MULTI CRITERIA DECISION SUPPORT
MODEL FOR THE TURKISH AIR FORCE
PERSONNEL COURSE/EDUCATION
PLANNING SYSTEM

THESIS

Cem Malyemez, First Lieutenant, TURAF

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DEPARTMENT OF THE AIR FORCE

AIR UNIVERSITY

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

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Cem Malyemez, B.S.I.E.

First Lieutenant, TURAF

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Cem Malyemez, B.S.I.E.
First Lieutenant, TURAF

Approved:

/signed/ 08 March 2011

Dr. Jeffery D. Weir (Advisor) Date

/signed/ 08 March 2011

Lt.Col. Stephen P. Chambal, PhD (Reader) Date

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Abstract

Many personnel are assigned to different courses and educational opportunities in the Turkish Air Force every year. This daunting process requires a great deal of time and does not currently seek to find an optimal solution. The Turkish Air Force has a database for all personnel information, but the officials use just a few quantitative personnel data points to complete their tasks. Moreover, the matching process is done by hand. Therefore there is a need for a model, which supports the Decision Makers, to cover the some of the other quantitative data points and also add some qualitative data for better decisions.

In this research, a value model for course/education assignments is developed. The multi criteria decision analysis method, Value Focused Thinking using the Analytic Hierarchy Process to determine value weights, is used to develop the model; and the Jonker-Volgenant Algorithm for linear assignment problems is used for the optimization phase of the problem. The use of the model is demonstrated by an example and the robustness of the model is tested by post optimality analysis.

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MULTI CRITERIA DECISION SUPPORT MODEL FOR THE TURKISH AIR FORCE PERSONNEL COURSE/EDUCATION PLANNING SYSTEM

I. Introduction

1.1 Background

"Genius without education is like silver in the mine." Benjamin Franklin

Personnel education is one of the most important subsystems of the human resource management system for both governmental and non-governmental organizations. There is nothing else like well educated personnel power. When we look at the history we can see that the countries, nations, militaries or any kind of organizations which are set up by uneducated people are obliged to lose. Education is a lifelong process and it is necessary for all people in the organization. Most organizations focus on strategic level personnel education more than the others, because the variation of this level of personnel can affect the whole organization.

The world is developing in every area of life including the military, and despite the changes of the war environment and the national security concept, the military is still so important for all countries. The famous British historian Sir Michael Howard states that the military profession is the most exigent of all the professions not only physically but intellectually as well (Murray, 2009). Because of the changes in the technology and in the world, the new military needs personnel who use their intelli-

gence more than in the past. As a conclusion of the new military concept, personnel can deal with working with different countries' personnel, making operations in diverse cultures and nations (Toffler and Toffler, 1993). The warfare is more complex now than it has ever been hitherto. Hence, military personnel have to be able to think analytically and always improve themselves. If you want to reach your goal or to be successful in today's competitive world, then you have to show your distinction more than the others. Thereby all militaries have to make their personnel more educated than the others which will make them more powerful. Recent United States Army research defines the nature of the future officer as: "An agile, adaptable, multi-skilled officer who leads in era of complexity and global, persistent conflict." (Barno, 2009).

Turkey is like a bridge between Europe and Asia which has hosted lots of different civilizations in history. Turkey is geographically close to countries and regions where lots of the world's problems are happening now. This unstable region makes the Turkish military more important to the country in its history and the Turkish Air Force (TURAF) is one of the most important services of the Turkish Armed Forces (TAF). For all of the reasons mentioned above the TURAF has to be organized with well educated personnel.

The TURAF is formed by different classes of personnel (e.g. officers, NCOs, civilians, specialists, etc.). Although each class has different career paths and course/education planning systems, this research focuses on the officer's course/education planning. The officers are in almost all of the managerial positions in the TURAF as in most of the other Air Forces. Thus the value of an officer's education level

might affect the whole organization more than the other classes of personnel. The main concern is going to be able to establish a helpful and effective decision support model. You can modify decision support models according to your demands by small changes. The important thing is to create the base model and necessary algorithm to solve it. Although we are going to gain insight of the officer's course/education planning system any organization even TURAF can use it for any class of personnel.

From this point forward, the term course is used instead of both course and educational facts. There are lots of courses in the TURAF human resource management system. Ergo, to choose the right personnel at the right time to the right course while thinking about his/her career plan and future positions is really a hard job for the related TURAF officials. The budget is also another significant part of this system. There can be changes in budget every year which makes the ongoing planning system more complex. Making all evaluations and calculations again and again is a time consuming process. The TURAF, which is a large organization, seeks to find the maximum utilization of this process.

In the TURAF, this process is managed by a department beneath the Personnel Directorate in the Air Force Headquarters. There are also branches, which are responsible for this work. The platoons are not involved in the selection process; they only inform the headquarters of the candidate personnel if necessary. All the workload for this important and challenging process is in hands of the branch which is called Individual Education Branch. The education is separated into two sections in this branch, in country and abroad. There are no different sections for personnel

specialties however. The courses that include flying are done by the Operation Directorate. Because of its different structure, the courses that are just for pilots are excluded from this research.

Currently, officials are evaluating personnel according to the relevant TURAF instructions by hand. The TURAF assigns approximately 3000 personnel to the courses every year. Selection process time changes with respect to the course's structure. When courses are thought about for more than one personnel, this planning process takes approximately 100 working days a year for the planning officials, and this time is just for first round elimination (Koc and Erman, 2010). Eventual selection can take more time because of the need to get approval from the other Directorates. This research is interested in just the time for the first round selection process.

This is a multi criteria assignment problem with a budget constraint. Conducting this process by manual assessments is daunting. The multi criteria optimization techniques make it easier and reduce the working hours spent for a manual solution.

1.2 Research Objectives, Assumptions, and Questions

The motivation of this research comes from the multi criteria assignment problem of the TURAF course/education planning system. Creating a new decision support model and finding the optimum personnel matches by taking into account the budget constraint is important for the TURAF. Using this model the manpower and budget will be used more efficiently and effectively. At present, assigning the per-

sonnel to the courses is executed manually and takes lots of time. We can show the difficulty of this problem with an example:

Given 15 personnel and 5 different courses and assuming all the personnel are eligible for all the courses, we have (15! / (15-5)!) or 360,360 different matches. It is impossible for a human alone to review all these possible matches.

With this model both the working hours of detailers and the effectiveness of results will be improved. Hence, the main goals of this research are to build and validate a multi criteria decision support model for decreasing the official's effort and maximize the utilization of results with respect to the benefit/cost ratio.

In this research, Value Focused Thinking(VFT) is used for both in approach to decision making process and evaluation of alternatives. This research builds a value hierarchy, which determines scores for both personnel and courses. It uses the weights of the measures of the value hierarchy. The weights of the measures in the value hierarchy are found by using the Analytic Hierarchy Process (AHP). It will have qualitative and quantitative factors together in the overall objective. This method is effective for complicated and unorganized decisions (Korkmaz et al., 2008).

The value hierarchy is built according to the TURAF Instruction with the help of subject matter of experts (SME). The value hierarchy is mutually exclusive and completely exhaustive. Personnel and course information can be found in databases of the organizations. The TURAF has a database for personnel information yet not the same thing for courses. Although there are too many courses, each course has

requirements in official documents. To build a database of courses is just a one time job and can be done easily. It is assumed that the TURAF can develop such a database.

In the current situation matches depend on the TURAF Instruction. The main concerns are to not violate the instructions and find the best personnel by looking at his/her information and requirements of the course. However, there is currently no quantitative approach in the process. There are some quantitative details used but they are evaluated qualitatively. This research develops a quantitative analysis process that uses scores for both personnel and courses. In this manner it will find the value of a match that is going to give the most benefit for the TURAF.

As we mentioned before cost is also important for this problem. Therefore, this method will find the benefit/cost ratio for the match. This number is used as the weight for a bipartite matching algorithm. This will give the best match for the TURAF including the consideration of cost. For the decision support model to be effective and efficient, it must be able enhance the value of matches and reduce the working hours spent to find good matches in the current position.

This research makes the following assumptions with respect to the given problem:

(a) For at least one course, there is an intersection among the personnel's course domain, which is a all set of courses for a given personnel, in a course pool.

(b) Personnel may be eligible for more than one course at a time.

(c) Exceptional situations (classified courses, special branches, etc.) are excluded from the scope of this research.

(d) Because of the privacy of the personnel data, random numbers are going to be used instead of actual data. The random data is well suited and there is no need to validate the data.

(e) Random data is also used for the cost of a course. The cost is same for all personnel who can be assigned to given course.

(f) Any course may be canceled from the assignment pool.

The Research Question:

Is there any way to build a robust, effective and efficient decision support model (DSM) which provides maximum utilization of the course/education planning system for the TURAF; includes the cost of a course; and reduces the number of hours worked by officials when accomplishing their tasks?

There are some other questions related to the main research question, such as:

- Why is it necessary to establish a decision support model?
- What are the shortcomings of the current system?
- How much time will be saved by using this model?
- Can the model improve effectiveness of the planning system?
- Which criteria can be used for the model?

- What can be added to the TURAF Instruction for making the model more useful?

1.3 Organization

Chapter 2 details multi criteria decision analysis and decision support models. Furthermore it discusses methods for solving multi criteria decision analysis problems. Chapter 3 describes the methodology used to solve the assignment matching problem with the verification of the matching algorithm. Chapter 4 describes the application of the methodology to both small and large scale problems. Chapter 5 states conclusions of the research and future work.

II. Literature Review

This section explains foundations and different methods of multi criteria decision analysis problems. First is a general background of multi criteria decision making problems, then assignment problems and finally decision support models.

2.1 Background

Decision Analysis (DA) is one of the most important subjects of the Operations Research (OR) community. Most DA problems have conflicting objectives; so decision makers have to make a decision in challenging situations which makes DA very important.

Multi Criteria Decision Analysis (MCDA) methods are applied to provide an analytical approach for compounding risk levels, values, and uncertainty and provide evaluation and ranking of many alternatives (Linkov and Steevens, 2010). MCDA is an inclusive, organized process for selecting the best or optimal alternative among the many alternatives. The acronyms, MADM (Multiple Attribute Decision Making), MODS (Multi Objective Decision Support), and MCDM (Multiple Criteria Decision Making) also are used for MCDA (Hajkowicz et al., 2000).

Hajkowicz and Higgins (2006) define the basic steps of the MCDA process as:

(a) Choose decision alternatives.

(b) Choose evaluation criteria.

(c) Create evaluation matrix based on performance measures.

(d) Transform into commensurate units.

(e) Weight the criteria.

(f) Rank the alternatives.

(g) Perform a sensitivity analysis if necessary.

(h) Make a decision.

In sensitivity or post optimality analysis, the variation of the results according to changes in the values or weights are examined (Janssen, 1992).

In MCDA, most of the methods have a similar approach to the decision making process; however they evaluate the alternatives in different ways. Different methods need different types of information and use various algorithms to find the optimal solution. The aim of MCDA methods is to reduce the complexity of the problem and help the decision maker (DM) make a decision which depends on his/her measures. An MCDA model needs at least two non dominated decision options.

Hipel (1992) describes the MCDA as:

$$X = \begin{pmatrix} x_{1,1} & \cdots & x_{n,1} \\ \vdots & \ddots & \vdots \\ x_{1,m} & \cdots & x_{n,m} \end{pmatrix}$$

n:decision options   m:criteria

Figure 2.1: MCDA Model Representation

This mxn matrix is called an effects table with m criteria and n alternatives. There is also a corresponding weight vector which shows the importance of each criteria. Hajkowicz et al. (2000) states the strengths and weakness of MCDA are as follows:

Strengths:

- Many methods can use both qualitative and quantitative data in any measurement units other than monetary.
- DMs find it logical because they already follow that process inadvertently.
- It establishes a good framework for problems that contain large and complex data, and this framework also improves the DM's understanding of a problem.
- It uses DM's values for weights and standardization which makes the process more obvious.
- It allows an interaction between DM and a model.
- Sensitivity analysis is available for MCDA.
- DMs can specify the level of complexity of the problem.

Weaknesses:

- Sometimes determination of weights is not understood by DM. This can cause a problem because the weights affect the results strongly.
- There are lots of MCDA methods and there is no clear guidance about choosing the methods. Different methods may conclude in different results.

- Some of the MCDA methods are so complex that can actually reduce the DMs understanding of the problem.
- Some methods need lots of inputs from DM and that can cause a time problem.
- Methods for compounding time into MCDA are still in process of development. We have to know the effect of time on our alternatives.

The assignment matching problem is one of the optimization problems in the area of OR. For big organizations the assignment process can be a confusing and time consuming subject. The assignment matching problem is the problem of selecting an optimal assignment of m elements (e.g., people or machine) to n positions (e.g., jobs or tasks), assuming that numerical values are given for each element's performance on each position. An optimal assignment is the one that maximize the sum of the element's values for their assigned positions for a given set of constraints (Munkres, 1957). The formulation of the personnel-assignment matching problem can be written as follow (Gass, 1985):

$$\max \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij} x_{ij} \tag{2.1}$$

subject to

$$\sum_{j=1}^{n} x_{ij} = 1 \qquad i = 1, 2, ..., m \tag{2.2}$$

$$\sum_{i=1}^{m} x_{ij} = 1 \qquad j = 1, 2, ..., n \tag{2.3}$$

$$x_{ij} \geq 0 \qquad \forall i, j$$

Model 1: Personnel Assignment Problem Formulation

$x_{ij} = 1$ if individual i is assigned to position j, 0 otherwise.

$c_{ij} =$ The value of assigning i to j.

Here the objective (2.1) is maximizing of the total value of assigning i to j. Constraint (2.2) denotes that individual i must only fill one job and constraint (2.3) denotes that position j must be filled by one individual i. Due to the structure of the problem integer values are going to be had for all the basic feasible solutions (Gass, 1985). In this research, constraint (2.2) and (2.3) have to have less than or equal to sign instead of equality, because every individual does not need to fill one of the positions, and there is no obligation for filling the all positions in the TURAF problem.

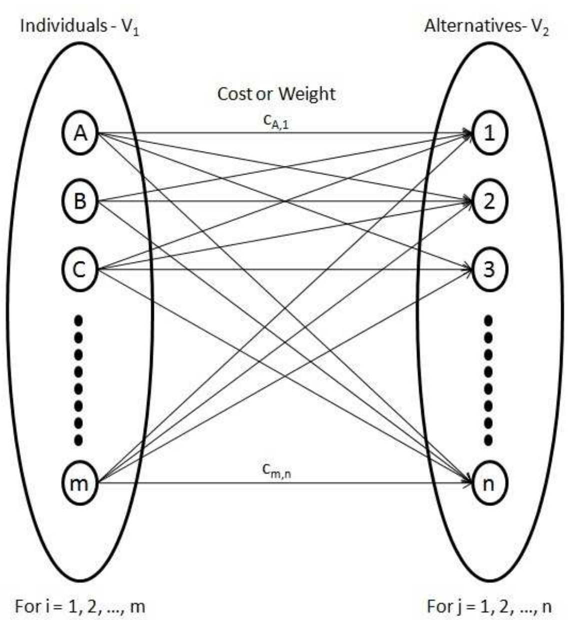

Figure 2.2: Bipartite Graph Representation

The personnel-assignment matching problem can be visualized by a bipartite graph with a set of disjoint vertices and edges. $G = (V_1, V_2, E)$, where the set of

vertices are disjoint such that $V = (V_1 \cup V_2)$ and every edge E has one end point in V_1 and the other end point in V_2 (Wolsey, 1998). A representation of a bipartite graph can be seen in Figure 2.2. In this graph V_1 represents a set of individuals and V_2 represents a set of positions and edges represent potential assignments with cost or weight (c_{ij}) of assigning an individual i to position j. There is no matching of individual to individual or position to position.

The most common way of formulating the bipartite assignment matching problem is as follows (Goemans, 2010):

$$\max(ormin) \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij} x_{ij} \tag{2.4}$$

subject to

$$\sum_{j=1}^{n} x_{ij} = 1 \qquad i \in V_1 = 1, 2, ..., m \tag{2.5}$$

$$\sum_{j=1}^{m} x_{ij} = 1 \qquad i \in V_2 = 1, 2, ..., n \tag{2.6}$$

$$x_{ij} \geq 0 \qquad \forall i, j$$

Model 2: Bipartite Assignment Matching Problem Formulation

The goal is to maximize the number of matches of individuals to positions while meeting the constraints that an individual must only fill one position (2.5) and a position must be filled by just one individual (2.6). As stated in personnel assignment problem formulation, again constraint (2.5) and (2.6) have to have less than or equal to sign due to the scope of this research.

With the evolution in computer technologies, DSMs and their applications have developed significantly. Because of the increase in the number of large organizations and globalization, decisions have become more complex, thereupon every area of life has started to need decision support more than in the past.

"MCDM research in the 1970s focused on the theoretical foundations of multiple objective mathematical programming and on procedures and algorithms for solving multiple objective mathematical programming problems During the 1980s, emphasis shifted toward the implementation of MCDM models on computers with the aid of decision support systems... Characteristics of multiple criteria decision support systems that are often absent from other types of decision support systems include analysis of multiple criteria, involvement of MCDM methods, and the integration of user input in the modeling processes..." (Dyer et al., 1992).

A DSM allows an interaction between the data and DM. Therefore a DSM must be user friendly. Technological innovations have also affected DSMs over time. Initially DSMs were started to help individual DMs but later were implemented for group decisions (Shim et all., 2002).

Especially for large scale and multi criteria problems, decision support is important because of the complexity of the problem. Nowadays most of the organizations are using computers in their jobs and that makes databases more accessible. Hence by using decision support models we can achieve satisfying results more easily.

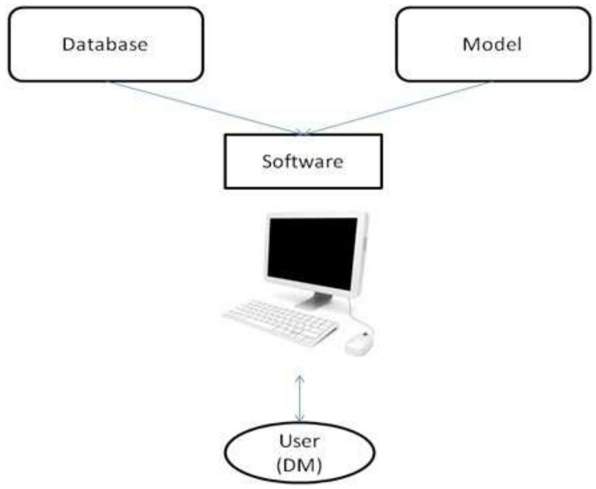

Figure 2.3: Decision Support System Components (Sprague and Carlson, 1982)

Power and Sharda (2007) classify decision support systems (DSS) according to their structures.

- Communications-driven.
- Data-driven.
- Document-driven.
- Knowledge-driven.
- Model-driven.

The meaning of these systems can also be seen by their names. A Communications-driven DSS is one that is driven from communications and information technologies. A Data-driven DSS is driven from data, managerial reports or analysis. A Document-driven DSS integrates a variety of storage and processing technologies to supply complicated document retrieval and analysis to support the DM. A Knowledge-driven

DSS is based upon knowledge that has been kept by using artificial intelligence or statistical tools. A Model-driven DSS includes computerized systems and also use optimization models to help the DM. It is interested in the manipulation of a quantitative model and so the model is the superior component in the DSS that renders the functionality for the DSS. This research uses a model-driven DSS. The model is going to be structured according to the multi criteria hierarchy. An optimization model is also going to be used in the model-driven DSS.

2.2 Multi Criteria Decision Analysis Methods

Multi Criteria Analysis is a process that uses weighted criteria to rank alternatives. MCDA determines the desirability of one alternative over the others according to criteria. In other words it tries to assist the DM with the problem according to his/her preferences and desires.

Howard (1991) states that methods for multi criteria decision analysis are procedures and mathematical algorithms for aiding decision making when multi criteria are considered. There are approximately 45 different MCDA methods (Nijkamp, 1989). Therefore, choosing the method can be important to achieve better conclusions.

MCDA methods are commonly grouped as discrete or continuous methods (Janssen, 1992). Discrete methods try to identify the most desirable alternative from a finite set of alternatives. On the other hand continuous methods try to identify an optimal alternative from an infinite number of feasible alternatives (Hajkowicz et al., 2000). Beside the discrete and continuous methods there are lots of different ideas about

subdividing the methods further. Discrete methods are suitable for this researches model. Seo and Sakawa (1988) classify discrete MCDA methods as analytical or judgmental methods. Janssen (1992) divides them into qualitative, quantitative or mixed methods.

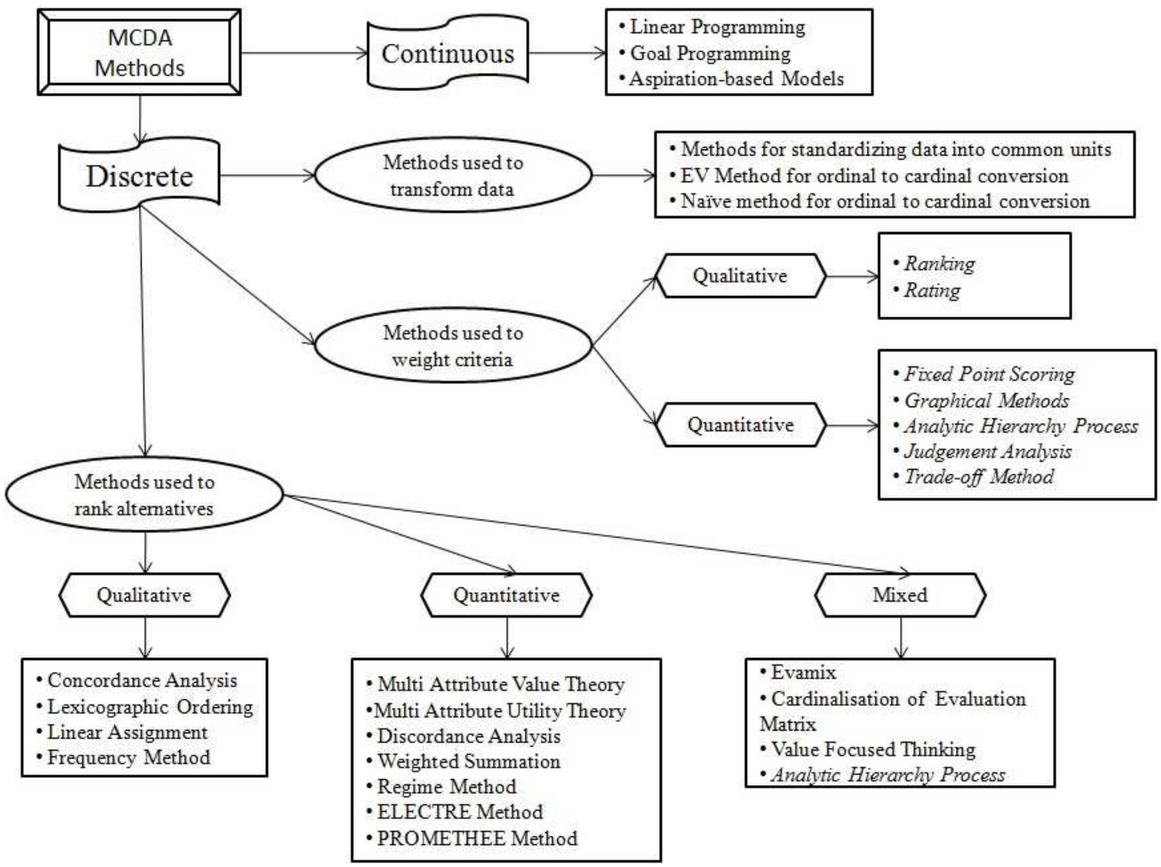

Figure 2.4: MCDA Methods Classification (Hajkowicz et al., 2000)

Hajkowicz et al. (2000) classify discrete methods based on function (Figure 2.4). Weighting the criteria, standardizing data values in the effects table and ranking the alternatives are determined as functions of MCDA. According to Seo and Sakawa (1988) the classification of analytic methods are shown in normal print and judgmental methods are shown in italics in Figure 2.4.

2.2.1 Goal Programming.

Many of the MCDA subjects are optimization related and goal programming is one of the most common techniques. The pros of goal programming is that these goals can be weighted according to DM preferences or some mathematical system (Lee and Schniederjans, 1983). It is typically used for assignment problems such as personnel assignment in military as in the research of Cimen (2001).

The mathematical formulation of goal programming is described as follows by Ananda and Herath (2009):

$$\text{Min z} = \sum_{i=1}^{n} P_i d_i^- + P_i d_i^+ \tag{2.7}$$

subject to

$$\sum_{j=1}^{n} a_{kj} x_j \leq b_k \qquad k = 1, 2, ..., s; i = 1, 2, ..., n \tag{2.8}$$

$$\sum_{j=1}^{n} \Omega_{ij} x_j + d_i^- d_i^+ = g_i \qquad i = 1, 2, ..., n \tag{2.9}$$

$$x_j, d_i^-, d_i^+ \geq 0 \qquad \forall i, j$$

Model 3: Goal Programming Formulation

Here x_j is the decision variable, P_i is a weighting function, d_i^- is the under achievement of the goal, d_i^+ is the over achievement of the goal, a_{kj} is the input-output coefficient between model constraint k and activity j, b_k is a model constraint, Ω_{ij} is the input-output coefficient between goal constraint i and activity j and g_i is a goal constraint. (2.7) is the function for minimizing the sum of weighted deviations

from the goal, (2.8) is the constraint equation for the model and (2.9) is the equation for the goal constraints.

2.2.2 *Weighted Summation.*

It is one of the most simple and commonly used methods of MCDA. In this method the criteria weights are multiplied with the standardized performance measures to obtain a value score. Therefore, the first step in the weighted summation method is standardizing the data. Two ways to standardize the decision variables are shown below (Ananda and Herath, 2009).

$$s_{ij} = \frac{x_{ij} - \min_j(x_{ij})}{\max_j(x_{ij}) - \min_j(x_{ij})} \tag{2.10}$$

$$s_{ij} = \frac{\max_j(x_{ij}) - x_{ij}}{\max_j(x_{ij}) - \min_j(x_{ij})} \tag{2.11}$$

Here s_{ij} is the standardized performance measure of the i^{th} alternative against the j^{th} criteria, x_{ij} is the performance measure for the i^{th} alternative against the j^{th} criteria, $\min_j(x_{ij})$ is the minimum performance measure for all alternatives against the j^{th} criteria and $\max_j(x_{ij})$ is the maximum performance measure for all alternatives against the j^{th} criteria. Equation (2.10) is for a criterion where more is better and Equation (2.11) is for criteria where more is worse.

An overall performance score is obtained for each alternative using the following formula (Hajkowicz et al., 2000):

$$v_i = \sum_{i=1}^{m} s_{ij} w_j \tag{2.12}$$

Equation (2.12) is the overall performance of alternative i, and w_j is the weight of criteria j. It is seen from the formulation that the weighted summation method can be used only when the weights information of data is available. Although commonly used, the weighted summation method makes some assumptions about the decision problem, which can cause inaccurate results. The assumptions of the weighted summation method are as follows (Rowe and Pierce, 1982):

- Value function for criteria must be linear.
- Criteria value functions must be on cardinal scales.
- Weights must be on a ratio scale.
- Each weight must represent the relative importance of a unit change in the value function.
- There must be additive independence among the preferences.

However this method has some shortcomings. Sometimes the objective function may be multiplicative instead of additive. The criteria transformation can be non-linear; often concave and convex forms more accurately capture DM preferences (Hajkowicz and Higgins, 2006).

2.2.3 Multi-Attribute Utility Theory. Multi-Attribute Utility Theory (MAUT) focuses on the alternatives on the side of risk and uncertainty. MAUT is based on the use of utility functions. Utility functions transform the values of the

alternatives into a dimensionless scale and therefore the more preferred alternative gets a higher utility value (Fulop, 2005).

In MAUT every criteria must be evaluated independently of the others and different overall functions can be used depending on the preferential independence assumptions (Seo and Sakawa, 1988). Keeney and Raiffa (1976, citied in Ananda and Herath, 2009) described the ways to check for utility independence as follows:

$$U(Y_1, ..., Y_n) = \sum_{i=1}^{n} k_i U_i(Y_i) \tag{2.13}$$

$$1 + KU(Y_1, ..., Y_n) = \prod_{i=1}^{n} [1 + K k_i U_i(Y_i)] \tag{2.14}$$

Equation (2.13) is for an additive function and Equation (2.14) is for a multiplicative function. Here U and U_i are utility functions scaled from zero to one, the k_i is a scaling constant with $0 < k_i < 1$, and $K > -1$ is a non-zero scaling constant. If a utility function is additive then $\sum_{i=1}^{n} k_i = 1$, and if it is multiplicative then $\sum_{i=1}^{n} k_i \neq 1$.

Even though these functions are generally believed to a provide better foundation of DM's preferences and demands, they are not often used because of the computational problems and long assessment time (Janssen, 1992).

2.2.4 ELECTRE Method. ELECTRE (Elimination and Choice Expressing Reality) method was defined by Bernard Roy in 1968 and is commonly used in French countries (Collette and Siarry, 2003). Ananda and Herath (2009) state that

this method shows the characteristics of the DM's preferences by pairwise concordance and discordance tables calculated for each criterion. The main idea is to find out the degree to which the scores and their associated weights affirm or oppose the dominant pairwise relationship among alternatives (Janssen, 1992).

The concordance index shows how much alternative a is better than alternative b with respect to the i^{th} criteria. On the other hand the discordance index shows that how much alternative a is worse than alternative b with respect to the i^{th} criteria. Both concordance and discordance indices lay between zero and one.

The concordance and discordance indices are defined by Ananda and Herath (2009) as follows:

$$c(a,b) = \frac{\text{Sum of weights for criteria where } a \geq b}{\text{Sum of weights for all criteria}} = \frac{\sum_{k \in A(a,b)} w_k}{\sum_k w_k} \tag{2.15}$$

$$d(a,b) = \frac{\text{Maximum interval where } b \geq a}{\text{Largest range of scale}} = max_k \frac{Z(b,k) - Z(a,k)}{k^\star} \tag{2.16}$$

Equation (2.15) is for the concordance index and Equation (2.16) is for the discordance index. Here $w(k)$ is the weight assigned to criteria k, $Z(b,k)$ is the evaluation of alternative b with respect to criteria k, $A(a,b) = k|$i is preferred to or equivalent to b, and $k^\star$ is the largest range among the K criterion vectors.

There are different types of the ELECTRE method, often referred to as ELECTRE I, ELECTRE II and ELECTRE III. Fulop (2005) says that ELECTRE I is used for partial ranking and to choose a set of alternatives while ELECTRE II is used for

ranking the alternatives. He states an outranking degree is established in ELECTRE III and this one is more complicated than the other ones because of its structure.

2.2.5 PROMETHEE Method.

PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluations) method was proposed by Brans and Vincke (1985). Basically this method has two different types. PROMETHEE I has been designed for partial ranking and PROMETHEE II for complete ranking. Ananda and Herath (2009) states there are three steps for the PROMETHEE methods.

- Define a preference function for each criterion.
- Defining a multi criteria preference index.
- Complete or partial ranking of alternatives.

Later on, Abu-Taleb and Mareschal (1995) described the fundamentals of the method as follows: First, a generalized criterion is developed to correspond to each of the k criteria. After that a preference function $P_i(x, y)$ may be defined which measures the DM's preference intensity for alternative a over alternative b for each criterion j. The function $P_j(a, b)$ lies in the interval $[0, 1]$. This function can be represented on a scale as below.

$P_j(a, b) = 0$ for indifference: $f_i(a) = f_i(b)$

$P_j(a, b) \sim 0$ for weak preference: $f_i(a) > f_i(b)$

$P_j(a, b) \sim 1$ for strong preference: $f_i(a) \gg f_i(b)$

$P_j(a, b) = 1$ for strict preference: $f_i(a) \ggg f_i(b)$

The difference in evaluations between alternative a and alternative b in terms of criterion j is defined as in Equation (2.17) and a preference function index is defined as in Equation (2.18):

$$d_j = f_i(a) - f_i(b) \tag{2.17}$$

$$\pi(a, b) = \sum_{j=1}^{k} w_j P_j(a, b) \tag{2.18}$$

where $w_j(j = 1, ..., k)$ are normed weights associated with the criteria, so that $\pi(a, b)$ also varies from 0 to 1. The following preference flows are then defined:

$$\text{The leaving flow} : \varphi^+(a) = \sum_{b \in A} \pi(a, b) \tag{2.19}$$

$$\text{The entering flow} : \varphi^-(a) = \sum_{b \in A} \pi(a, b) \tag{2.20}$$

$$\text{The net flow} : \varphi(a) = \varphi^+(a) - \varphi^-(a) \tag{2.21}$$

The larger $\varphi(a)$, the better the alternative a is. Therefore this flow provides a complete ranking of the alternatives.

2.2.6 Analytic Hierarchy Process. The Analytic Hierarchy Process, introduced by Saaty (1977, 1980), is a widely used MCDA method and probably the most popular in many areas. The purpose of AHP is to help DMs in organizing their values and judgments to make more effective decisions and transfer them into quantitative ratios (Saaty, 1994). So, AHP combines both qualitative and quantitative

data together for better decisions. In AHP a hierarchy is created, which consists of criteria and sub-criteria and an overall objective at the top.

The methodology of AHP is based on pairwise comparison. It tries to define how important is criterion a with respect to criterion b. The DM makes pairwise comparisons of all criteria in the hierarchy using a 1-9 scale. Fulop (2005) explains this scale as follows:

1 = Equal importance or preference.

3 = Moderate importance or preference of one over another.

5 = Strong or essential importance or preference.

7 = Very strong or demonstrated importance or preference.

9 = Extreme importance or preference.

Generally the pairwise comparison data can be analyzed in two ways, regression analysis or an eigenvalue technique. Saaty's original method is based on the eigenvalue technique. Ananda and Herath (2009) explain that the right eigenvector of the largest eigenvalue of matrix A, which is shown below, constitutes the estimation of relative importance of attributes. The pairwise comparison matrices take the following form:

$$A = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{pmatrix}$$

where a_{ij} represents the pairwise comparisons rating for criteria i to j. $n(n-1)/2$ pairwise comparisons are needed for a nxn matrix. Saaty (1977) proposed the right eigenvector method that constructs the vector of priority weights and facilitates testing for inconsistency. In the case of perfect consistency,

$$AW = nW \tag{2.22}$$

where A is the nxn comparison matrix and $W = (w_1, w_2, ..., w_n)^T$ is the preference weightings of each criteria. Saaty (1977) proposed the following definition;

$$AW = \lambda_{max} W \tag{2.23}$$

where λ_{max} is the maximum eigenvalue of matrix A. Saaty (1977, 1980) proved that the largest eigenvalue λ_{max} is always greater than or equal to n. This approach can cause a problem when n is large, because the comparisons can take a lot of time and can be costly. The regression analysis approach, which allows for small amounts of comparisons was generated for avoiding the difficulties of the eigenvector approach (Kolehmainen, 2010).

Saaty (1994) explains the difference between AHP and utility theory. Utility theory must answer the question: how many units of one attribute can be traded off with how many units of another? On the other hand, in AHP the question generally

is: which of two attributes is more important, preferred or liked with respect to a higher level attribute?

Despite its wide usage there are some critics of the AHP method. The number of comparisons, the comparison scale, and rank reversal are the main criticisms (Kangas and Kangas, 2005). Although it has some problems, it is really easy to use and understand and it allows for qualitative data to be put into the model.

2.2.7 Value Focused Thinking. Generally there are two kinds of conventional approaches for decision analysis problems, alternative-focused and value-focused. The general method for decision analysis is to choose one of the initial set of alternatives, and Keeney (1992) refers to this as Alternative Focused Thinking (AFT). The decision in AFT is only good within given set of alternatives, but the goodness of decision for the problem is not known specifically. Alternatives are absent for to achieve the values. Thus decision analysis process first should focus on values and then alternatives to reach that values. This manner of approach is called as Value Focused Thinking (VFT) (Keeney, 1992, 1994, 1996). The benefits of VFT are shown in Figure 2.5.

Keeney (1992) states that VFT provides a much more robust methodology for not only solving existing problem but also for uncovering the possible future problems. There are different ways to implement VFT to the multi objective/criteria decision analysis problems. Weir (2010) defines the VFT process in ten steps, which has flexible order.

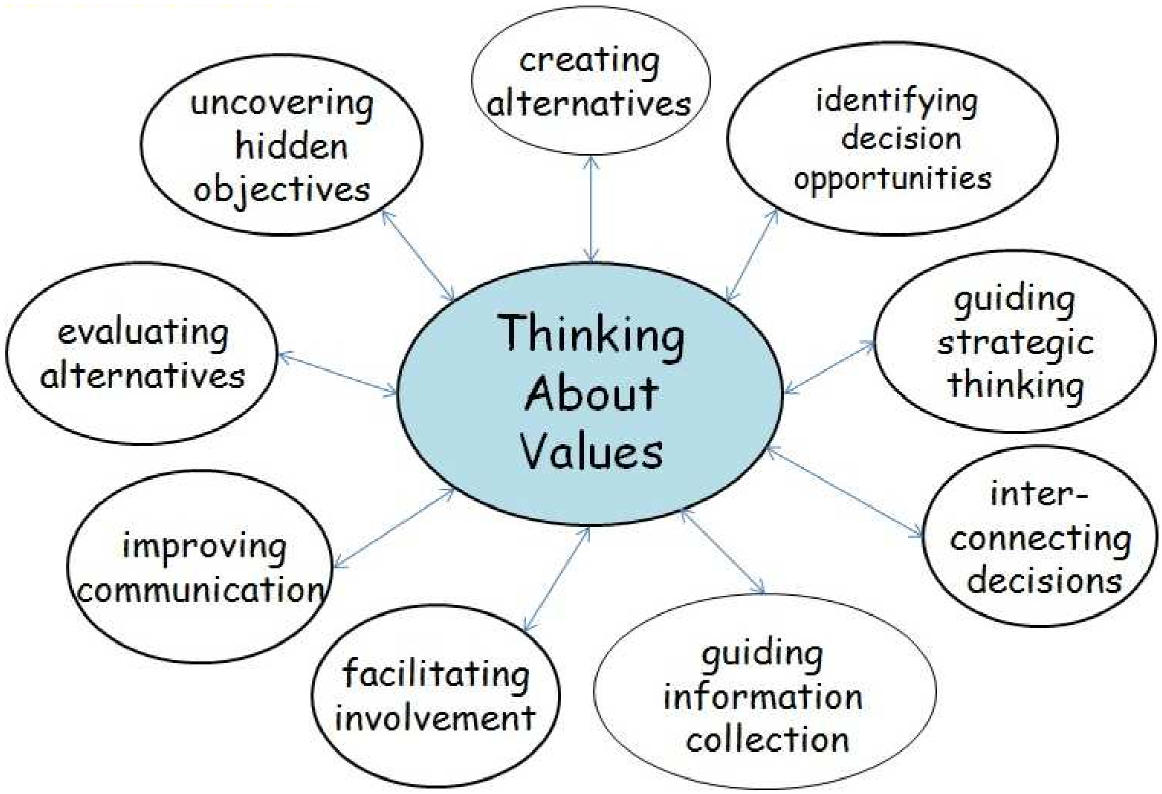

Figure 2.5: Benefits of VFT (Keeney, 1992, 1994)

- Problem identification.
- Creating the value hierarchy.
- Developing the measures.
- Define Single Dimensional Value Functions (SDVF).
- Weighting the hierarchy.
- Alternative generation.
- Scoring the alternatives.
- Deterministic analysis.
- Sensitivity or post optimality analysis.

- Conclusions and recommendations.

As seen from the steps VFT use both qualitative and quantitative data together. Providing mathematical approach, structured decision support, being objective and repeatable, discussions at the low level are the pros; subjectivity, influence of bad experiences, and easy to manipulate the numbers are the cons of VFT (Weir, 2010). Different VFT experiences show thinking about the strategic objectives and values should get easier and conclude in better decisions (Keeney, 1994).

There are also other types of MCDA methods like *aspiration level approaches* which use a variety of multi objective goal programming techniques, *fuzzy methods* which use imprecise and uncertain information, *descriptive methods* which examine the relationships between the attributes or variables in statistical terminology, *hybrid methods* which are combination of two or more MCDA method (Ananda and Herath, 2009).

2.3 Research Contribution

MCDA applications are in use in many different disciplines such as economics, psychology, statistic, and forestry. The Literature, however, seems to be lacking in any research about personnel course/education planning system optimization or decision support models.

There is some research about the personnel assignment problem but usually they use MCDA very sparingly. The research of Korkmaz et al. (2008) is closest to this research concept. They looked for an analytic hierarchy process and bipartite

matching based decision support system for the military personnel assignment problem. They developed a simple computer program, which is called ADES, for solving this complex problem. Their basic steps are:

Step-1 Form a criteria hierarchy for having the right people in the right jobs.

Step-2 Differentiate the relative importance of the criteria by making pairwise comparisons (AHP) for each position.

Step-3 Define the personnel information related to the criteria for each personnel.

Step-4 Create the position preferences by using position information and personnel information.

Step-5 Input the personnel preferences.

Step-6 Make the assignment by bipartite matching.

This research differs from their research in the value hierarchy and functions; however because of the similarities in the personnel data some common criteria may be used. Moreover this research is also going to consider the cost of the assignments. Personnel preferences are not going to be used in this research. Specifically this research finds the maximum value of personnel - course/education matches for an organization while taking into consideration the cost.

The next chapter presents the methodology of this research and model verification.

III. Methodology

This chapter explains the methodology that is used to solve the TURAF personnel course/education planning problem. First, it builds a criteria hierarchy that belongs to the problem. Then it determines the measures and value functions used. After that it uses AHP to determine the weights of the criteria. Then it will solve two optimization problems from two sub-problems of the main problem, maximum number of matches and maximum weighted value . Since the problem is formulated as bipartite structure, the Jonker-Volgenant Algorithm for the linear assignment problem is used for optimization. Finally, this chapter discusses the verification of the model.

3.1 Background

Recall the motivation of this research is to assign the most appropriate personnel from the TURAF to a course. The solution approach uses a multi criteria decision analysis method, VFT, and bipartite matching. VFT provides structured decision support including qualitative and quantitative data. AHP is used in weighting the value hierarchy. Bipartite matching is one of the assignment matching algorithms, which is also known as two sided matching. This problem has m personnel in one side, and n courses on the other side. The objective of the TURAF is to maximize the value of the overall matching of personnel and courses. The cost is also going to be considered while finding the value. In the TURAF, the courses are grouped as abroad and in country, but both of them have the same structure.

3.2 Model Formulation

3.2.1 Criteria Hierarchy.

This research structures the criteria hierarchy according to the TURAF instructions and opinions of SMEs. There is an overall objective at the top of the hierarchy and there are some main criteria and sub-criteria under this objective. While most of the criteria are the same, for the in country courses the language score and day point score are not used.

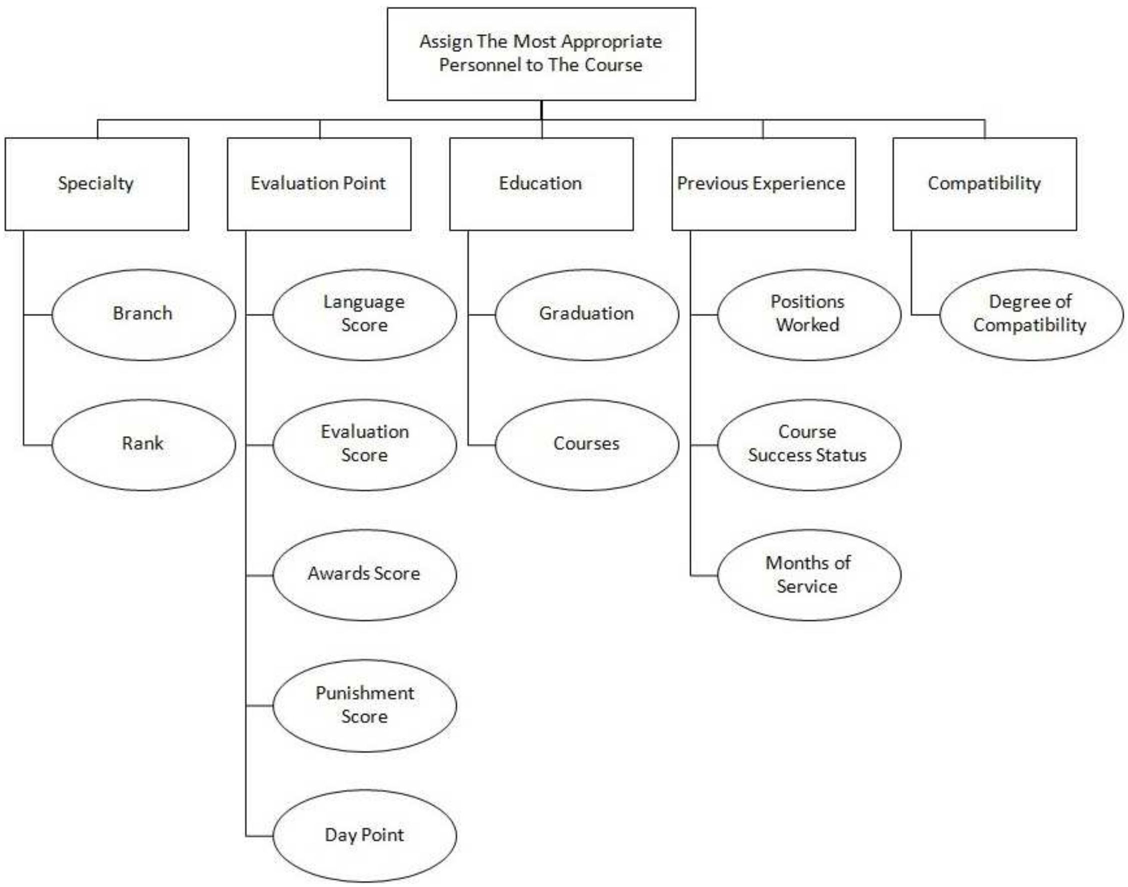

Figure 3.1: Criteria Hierarchy

This hierarchy has five main criteria and 13 sub-criteria. The five main criteria are a grouping of the sub-criteria, thus explanation of sub-criteria will help in the understanding of the general structure of the hierarchy.

Branch: There are more than 20 branches in the TURAF such as pilot, maintenance, intelligence, communication, personnel, acquisition,...etc. This research only considers eight branches and represents them as Branch-1, Branch-2,...,Branch-8 instead of their real names.

Rank: This research is interested in officer's course/education planning, so six ranks are used. Again Rank-1, Rank-2,..., Rank-6 codes are used in the name of the actual ranks.

Language Score: There is an official test for all government workers for foreign languages in Turkey. This test is used for selection criteria in most of the application procedures. Applicants have to be above 60 to be eligible for the selection process, and the maximum score is 100.

Evaluation Score: Every person in the TURAF is evaluated yearly and these scores are saved in the personnel records. Applicants must be above 90 for to be eligible for the course/education assignment process according to TURAF instructions. The maximum evaluation score is 100.

Awards Score: Every person will get a written appreciation or pin for their service sometime in their active duty life. There is a general chart for calculation of their awards score in the TURAF.

Punishment Score: It is similar to awards points. If a person receives punishment, then his/her evaluation points are effected according to a general chart for calculation of a punishment score. The punishment score has a negative effect.

Day Point: This is from the TURAF instruction about courses. If an applicant has been abroad before then this will affect his/her overall score negatively. There are three categories of countries which have coefficients of 1, 0.9 and 0.7. Day point is calculated by (Number of days abroad x 0.05 x country coefficient).

Graduation: It is the highest education level a person has achieved. The possibilities are University, Master Degree and PhD.

Courses: It is the number of courses that were taken after joining the military for a given person. The applicant who has not been assigned or has been assigned to fewer courses than the other applicants has a priority according to the TURAF instruction.

Positions Worked: There are many different positions in the TURAF. This research classifies these positions as technical level, tactical level, and strategic level. Position-1 represents technical level, Position-2 represents tactical level, and Position-3 represents strategic level.

Course Success Status: This is the average of a person's previous course grades. An applicant must have an average above 60 to being eligible for the selection process according to the TURAF instruction.

Months of Service: Total number of months of military service.

Degree of Compatibility: It is the compatibility between the alternative and the applicant's career plan.

3.2.2 Value Functions.

After building the hierarchy the next step is to create the value functions. This research was implemented by using the Hierarchy Builder (Weir, 2008) software. Value functions were determined by the inputs of SMEs and the TURAF instructions. This research uses seven categorical and six continuous value functions for the model. Next, one example of each type of function is explained. All the other functions are shown in Appendix-A.

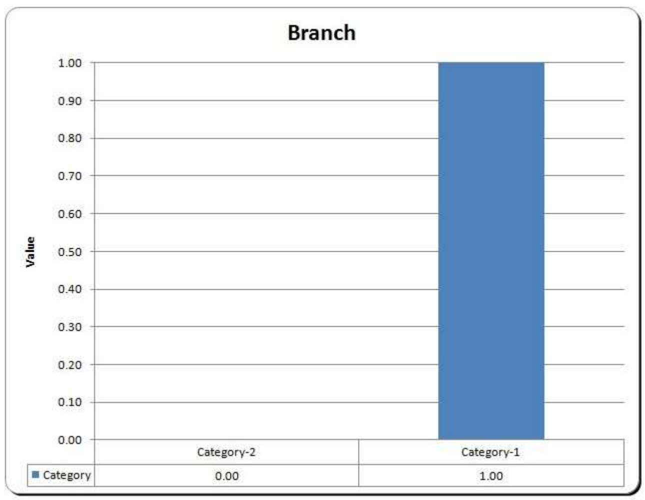

Figure 3.2: Value Function of Branch

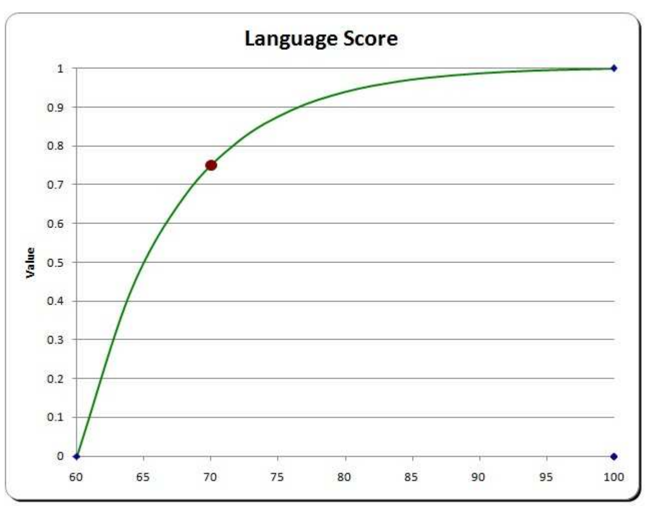

Figure 3.3: Value Function of Language Score

Figure 3.2 is an example of a categorical value function and Figure 3.3 is an example of continuous value function. In categorical value functions the most preferred category has value of 1 and the least preferred category has value of 0. Therefore course's most preferred branch or branches will be in Category-1 and the rest of the branches will be in Category-2 in Figure 3.2. The continuous value functions are classified as increasing and decreasing functions. In increasing functions, the minimum score has value of 0 and maximum score has value of 1. However, in the decreasing functions the lowest score has value of 1 and the highest score has value of 0. Language score lies between 60 and 100 in Figure 3.3. The break points and shapes of the functions are determined by the inputs of SMEs.

3.2.3 Weighting the Hierarchy. The AHP method was used for weighting the hierarchy. The pairwise comparisons were done by SMEs in the TURAF Headquarters. The abroad and in country hierarchies have different weights as they were weighted separately. The weights are shown in Table 3.1.

Saaty (1980) indicates that a consistency ratio less than 0.1 does not affect the ratings too much. This consistency ratio is calculated automatically by the Hierarchy Builder (Weir, 2008) software. All weights for this research we are consistent.

3.2.4 Overall Score and Benefit/Cost Ratio. Once all of the data is input, an additive value function is used to calculate the overall value of a specific assignment. Next the benefit/cost ratio is calculated.

Table 3.1: Weights of Criteria

Criteria	Abroad	In Country
Branch	0.094	0.064
Rank	0.047	0.064
Language Score	0.096	–
Evaluation Score	0.122	0.343
Awards Score	0.041	0.088
Punishment Score	0.031	0.038
Day Point	0.238	–
Graduation	0.014	0.023
Courses	0.029	0.046
Positions Worked	0.010	0.051
Course Success Status	0.039	0.032
Months of Service	0.039	0.020
Degree of Compatibility	0.200	0.229

As in all militaries, the TURAF has funds for expenses. The fund for courses and education is used for not only that but also for other demands. Therefore analysis of this resource allocation is important. The Benefit/Cost Ratio is a widely used method because it shows the cost per unit value. For this research it can be calculated by simply dividing the benefit (overall value from the model) of an applicant for a given course to the cost of that course. Next, the benefit/cost ratio is normalized to overcome the small ratios that are generated.

3.2.5 Assignment Matrix. This research uses two types of assignment matrices. The first is formed by just 0's and 1's which shows the feasible matches. If

personnel i can be assigned to course j, this element of the matrix will have value of 1 otherwise a value of 0. The second matrix for the optimization algorithm is formed by the normalized benefit/cost ratios of each personnel-assignment match. In both matrices rows represent the personnel and columns represent courses.

3.3 Optimization Phase

3.3.1 General. The values in an assignment matrix are the costs or weights of assigning personnel i to course j. Because of the unimodular property of the constraints and linearity in the objective function, a Linear Programming (LP) problem will solve the problem and result in an all integral solution.

3.3.2 Sets, Parameters, and Decision Variables. Before the mathematical formulation, sets, parameters, and decision variables need to be defined.

Table 3.2: Parameters, Sets, and Decision Variables of Model

m	Total number of personnel in a given selection process
n	Total number of courses in a given selection process
$i = 1, 2, ..., m$	The set of personnel in a given selection process
$j = 1, 2, ..., n$	The set of courses in a given selection process
s_{ij}	Score of assigning personnel i to a course j
c_j	Cost of course j
v_{ij}	Normalized value of assigning personnel i to a course j
X_{ij}	Decision variable. 1 if personnel i can be assigned to course j, 0 otherwise
Z	Maximum number of assignments for all personnel in i to the courses in j
W	Maximum weighted assignments for all personnel in i to the courses in j
R_{ij}	The matrix which is set up by ratio s_{ij} to c_j (s_{ij}/c_j)
r^*	The maximum element of matrix R_{ij}

3.3.3 Problem Formulation. This research divides the problem into two sub-problems. The first one finds the maximum matching and the second one

finds the maximum weighted value. Two problems are used to see if the maximum weighted matching is also a maximum matching. After solving this problem the DM has to decide which way s/he wants to choose, maximum matches but less value or the maximum value but less matches. In this research, all maximum weighted matches were also maximum matching, but this cannot be guaranteed in general.

In Sub-problem(1) the objective is to find the maximum matches between personnel and courses. The value of these matches is found by adding the weights of matched pairs.

$$\text{Max Z} = \sum_{i=1}^{m} \sum_{j=1}^{n} X_{ij} \tag{3.1}$$

subject to

$$\sum_{i=1}^{m} X_{ij} \leq 1 \qquad j = 1, 2, , n \tag{3.2}$$

$$\sum_{j=1}^{n} X_{ij} \leq 1 \qquad i = 1, 2, , m \tag{3.3}$$

$$X_{ij} \in \{0, 1\} \qquad \forall i, j$$

Model 4: Sub-problem(1) Formulation

In Sub-problem(2) to the objective is to find the maximum weighted value of the matches.

$$\text{Max W} = \sum_{i=1}^{m}\sum_{j=1}^{n} v_{ij}X_{ij} \tag{3.4}$$

subject to

$$\sum_{i=1}^{m} X_{ij} \leq 1 \qquad j = 1, 2, , n \tag{3.5}$$

$$\sum_{j=1}^{n} X_{ij} \leq 1 \qquad i = 1, 2, , n \tag{3.6}$$

$$X_{ij} \in \{0, 1\} \qquad \forall i, j$$

Model 5: Sub-problem(2) Formulation

3.3.4 Jonker-Volgenant Algorithm for Linear Assignment Problem. Instead of solving this LP problem, this research uses the Jonker-Volgenant Algorithm to solve the weighted bipartite matching problem. The Jonker-Volgenant Algorithm for the linear assignment problem, which is based on shortest augmenting path, was developed by Jonker and Volgenant (1987). Generally, the Jonker-Volgenant Algorithm solves minimization problems, but can be converted to solve maximization problems by multiplying the assignment matrix by -1 or by subtracting each element of assignment matrix from the maximum value of the matrix. This algorithm can be used for both square and rectangular matrices. It is faster than the most of the other linear assignment algorithms (Jonker and Volgenant, 1987).

In this research, both sub-problems are maximization problems and are not square matrices since the number of courses always will be less than the number of personnel. The algorithm was implemented in MATLAB (Mathworks, R2010a) and the codes for solving Sub-problem(1) and Sub-problem(2) using the Jonker-Volgenant

Algorithm are in the Appendix-B. This MATLAB code was written by Cao (2011) and was changed only to work with the sub-problem structures.

3.3.5 Post Analysis.

After finding the optimal solutions, a new question can be considered. How good is the solution? This research considers two kinds of goodness, goodness of the personnel pool and goodness of algorithm's solution. There are two different values for comparison. First, what is the maximum value that can be achieved by these costs if every personnel had an overall score of 1, and second find the maximum value that can be achieved by assigning the highest valued personnel in relation to a course to the course. The formulations for these calculations are shown in Equation 3.7 and 3.8 respectively.

$$\sum_{j=1}^{n} \frac{\left(\frac{1}{c_j}\right)}{r^*} \tag{3.7}$$

$$\sum_{j=1}^{n} \left(\max_{i} \left(\frac{R_{ij}}{r^*} \right) \right) \tag{3.8}$$

The ratio of Equation 3.8 to Equation 3.7 shows the goodness of whole personnel pool. The ratio of value which is found by optimization algorithm to value found by Equation 3.8 shows the goodness of model.

3.4 Verification

To verify the matching algorithm produced the correct results when MATLAB solved each problem, previously solved small problems were used to compare the algo-

rithm output against known solutions. The problem was solved by MATLAB (Mathworks, R2010a) for all instance matrices. If both results were equal in terms of assignments and values then the algorithm was considered successful. This procedure was repeated for 10 times and in every case, previous solutions and Jonker-Volgenant matching algorithm were equal to one another.

In the next chapter, this methodology is applied to the TURAF's problem.

IV. Application, Results, and Analysis

In this chapter, the results of using the methodology from Chapter 3 on the TURAF's problem are presented. Because of the privacy of actual personnel data and not being able to gather some of the data from current TURAF databases, randomly generated data is used and analyzed according to the model in Chapter 3. Detailed analysis of a problem containing 20 courses and 50 personnel is explained in the next sections.

All of the analysis in this research was performed on a computer with an Intel(R) Core(TM) i7 CPU Q740 @1.73GHz Processor, 8 GB RAM, Windows 7 Home Premium 64-bit operating system. The optimal solutions were found using MATLAB (Mathworks, R2010a).

4.1 Courses' Requirements

The model developed in this research has 13 criteria. Nine of the criteria; language score, evaluation score, awards score, punishment score, day point, courses, course success status, months of service, and degree of compatibility; have the same SDVF regardless of the personnel-course matching. Four of the criteria branch, rank, graduation, and positions worked, have different SDVFs depending on the course/education requirements found in TURAF instructions. Abroad and in country SDVFs requirements are shown in different tables.

Table 4.1: Abroad Courses' Requirements

	Branch		*Rank*			*Graduation*			*Positions Worked*	
Course	*Category-1*	*Category-2*	*Category-1*	*Category-2*	*Category-3*	*Category-1*	*Category-2*	*Category-3*	*Category-1*	*Category-2*
Course-1	**B-1**	**others**	**R-2,R-3**	**R-4**	**others**	**Master**	**PhD**	**University**	**P-1**	**others**
Course-2	**B-1**	**others**	**R-2,R-3**	**R-4**	**others**	**Master**	**PhD**	**University**	**P-1**	**others**
Course-4	B-1,B-2,B-4	others	R-3	R-4	others	Master	PhD	University	P-2	others
Course-7	**B-2**	**others**	**R-3,R-4**	**R-5**	**others**	**Master**	**PhD**	**University**	**P-2**	**others**
Course-9	B-5,B-7	others	R-5	R-6	others	PhD	Master	University	P-3	others
Course-10	B-1,B-2	others	R-2,R-3	R-4	others	Master	PhD	University	P-2	others
Course-11	B-1,B-2	others	R-2,R-3	R-4	others	Master	PhD	University	P-2	others
Course-15	B-3	others	R-3	R-4	others	Master	PhD	University	P-2	others
Course-16	**B-6**	**others**	**R-2,R-3**	**R-4**	**others**	**Master**	**PhD**	**University**	**P-1**	**others**
Course-19	B-1,B-3	others	R-3,R-4	R-2	others	Master	PhD	University	P-2	others
Course-20	B-4	others	R-4	R-5	others	PhD	Master	University	P-3	others

Table 4.2: In Country Courses' Requirements

	Branch		*Rank*			*Graduation*			*Positions Worked*	
Course	*Category-1*	*Category-2*	*Category-1*	*Category-2*	*Category-3*	*Category-1*	*Category-2*	*Category-3*	*Category-1*	*Category-2*
Course-3	B-4,B-5,B-8	others	R-3,R-4	R-2	others	PhD	Master	University	P-2	others
Course-5	**B-1**	**others**	**R-4,R-5**	**R-6**	**others**	**PhD**	**Master**	**University**	**P-3**	**others**
Course-6	**B-1**	**others**	**R-4,R-5**	**R-6**	**others**	**PhD**	**Master**	**University**	**P-3**	**others**
Course-8	B-6	others	R-3,R-4	R-5	others	Master	PhD	University	P-2	others
Course-12	B-1,B-2,B-3	others	R-2,R-3	R-4	others	Master	PhD	University	P-1	others
Course-13	B-1,B-2,B-3	others	R-2,R-3	R-4	others	Master	PhD	University	P-1	others
Course-14	B-1,B-2,B-3	others	R-2,R-3	R-4	others	Master	PhD	University	P-1	others
Course-17	B-5,B-7,B-8	others	R-2	R-1	others	Master	PhD	University	P-1	others
Course-18	B-5,B-7,B-8	others	R-2	R-1	others	Master	PhD	University	P-1	others

In these tables, "B" represents branch, "R" represents rank, and "P" represents position. The courses in bold are those in which nobody can be assigned to that course other than those personnel in Category-1 in the branch criteria. As seen, some courses have the same requirements, which means they belong to the same course there are as many of them as there are quotas for that course.

4.2 Personnel Data

50 sets of personnel data was randomly generated using Microsoft Excel (Office Home and Student, 2007). After the random generation, some values were manipulated to make the data more representative of the real world data. The general personnel data is shown in Table 4.3. There are 12 criteria values for personnel data. The degree of compatibility criteria is not included in the general personnel data. Because 12 criteria values are the same for every courses, but personnel degree of compatibility data is changed according to the course. Therefore that criteria was generated for every course separately.

4.3 Personnel Scores

When the personnel data is input in the model, Hierarchy Builder (Weir, 2008) gives an overall value for each personnel for a particular course and ranks them all. The ranking can be displayed both graphically and numerically. Course 1, 2, and 3 personnel score rankings' graphical representations are shown in Figure 4.1 and 4.2 as an example. Course 1 and 2 are the same course, so they have the same rankings. In the Figure 4.1 and 4.2 "P" represents Personnel.

Table 4.3: Personnel Data

Personnel	Branch	Rank	Language Score	Evaluation Score	Awards Score	Punishment Score	Day Point	Graduation	Courses	Positions Worked	Course Success Status	Months of Service
Personnel-1	Branch-1	Rank-3	67	98.36	2.26	0.00	0	University	Two or More Courses	Position-2	79	117
Personnel-2	Branch-2	Rank-3	81	95.84	2.36	0.00	18	Master	Two or More Courses	Position-2	66	166
Personnel-3	Branch-4	Rank-2	92	99.01	2.14	0.00	0	Master	Two or More Courses	Position-3	94	48
Personnel-4	Branch-3	Rank-4	71	94.84	2.56	0.10	0	Master	One Course	Position-1	87	210
Personnel-5	Branch-1	Rank-3	92	100.00	2.11	0.00	14	University	No Course	Position-1	61	159
Personnel-6	Branch-5	Rank-5	91	96.96	3.84	0.16	21	University	No Course	Position-2	93	273
Personnel-7	Branch-6	Rank-4	78	100.00	3.21	0.00	0	Master	Two or More Courses	Position-2	60	233
Personnel-8	Branch-1	Rank-3	92	98.24	1.65	0.00	4	University	Two or More Courses	Position-1	74	164
Personnel-9	Branch-6	Rank-2	75	100.00	2.30	0.00	0	Master	Two or More Courses	Position-1	95	49
Personnel-10	Branch-4	Rank-5	82	96.05	2.98	0.34	10	PhD	Two or More Courses	Position-3	83	271
Personnel-11	Branch-7	Rank-4	80	97.33	3.63	0.00	0	University	No Course	Position-2	88	229
Personnel-12	Branch-4	Rank-3	97	98.22	2.99	0.00	10	University	No Course	Position-3	94	138
Personnel-13	Branch-1	Rank-4	100	100.00	2.30	0.36	24	University	No Course	Position-2	73	211
Personnel-14	Branch-1	Rank-6	85	98.30	3.33	0.08	4	PhD	No Course	Position-2	91	293
Personnel-15	Branch-5	Rank-2	83	100.00	2.77	0.00	15	Master	No Course	Position-1	87	74
Personnel-16	Branch-6	Rank-3	74	99.23	1.34	0.00	0	University	Two or More Courses	Position-3	75	148
Personnel-17	Branch-7	Rank-2	90	99.96	1.50	0.00	0	Master	No Course	Position-1	89	39
Personnel-18	Branch-8	Rank-2	63	98.67	0.89	0.00	0	Master	One Course	Position-1	91	93
Personnel-19	Branch-3	Rank-1	82	97.65	0.67	0.00	2	Master	Two or More Courses	Position-3	91	15
Personnel-20	Branch-2	Rank-4	88	92.23	2.95	0.00	11	PhD	One Course	Position-1	93	196
Personnel-21	Branch-1	Rank-4	89	96.77	2.67	0.68	10	PhD	Two or More Courses	Position-1	100	232
Personnel-22	Branch-7	Rank-5	76	98.63	2.50	0.63	0	Master	No Course	Position-3	76	254
Personnel-23	Branch-3	Rank-2	93	100.00	1.91	0.00	12	Master	No Course	Position-2	98	107
Personnel-24	Branch-2	Rank-3	91	95.98	2.95	0.08	9	Master	One Course	Position-3	70	120
Personnel-25	Branch-5	Rank-3	98	95.94	2.46	0.40	14	PhD	One Course	Position-2	85	121
Personnel-26	Branch-4	Rank-3	70	99.63	2.64	0.08	21	PhD	One Course	Position-2	93	169
Personnel-27	Branch-8	Rank-6	100	95.96	3.24	0.34	57	PhD	Two or More Courses	Position-2	88	320
Personnel-28	Branch-1	Rank-4	69	100.00	2.76	0.00	0	University	No Course	Position-2	61	205
Personnel-29	Branch-1	Rank-1	64	98.03	1.12	0.09	0	University	Two or More Courses	Position-1	78	12
Personnel-30	Branch-6	Rank-2	93	94.76	2.97	0.78	15	Master	No Course	Position-1	82	104
Personnel-31	Branch-5	Rank-2	95	100.00	2.56	0.00	6	University	Two or More Courses	Position-3	95	101
Personnel-32	Branch-3	Rank-4	85	96.72	2.45	0.66	0	Master	One Course	Position-1	68	229
Personnel-33	Branch-7	Rank-2	76	100.00	1.63	0.00	4	Master	Two or More Courses	Position-1	85	70
Personnel-34	Branch-2	Rank-1	96	95.96	0.24	0.62	0	Master	No Course	Position-2	100	22
Personnel-35	Branch-3	Rank-3	100	97.09	3.12	0.13	11	PhD	No Course	Position-3	87	110
Personnel-36	Branch-6	Rank-2	79	98.22	2.10	0.12	0	Master	Two or More Courses	Position-1	80	81
Personnel-37	Branch-4	Rank-4	92	98.24	2.58	0.27	0	Master	One Course	Position-2	79	207
Personnel-38	Branch-2	Rank-3	79	94.87	2.45	0.40	8	University	One Course	Position-1	92	178
Personnel-39	Branch-1	Rank-2	75	99.69	1.92	0.00	0	University	One Course	Position-1	70	67
Personnel-40	Branch-8	Rank-3	85	100.00	1.53	0.00	0	Master	No Course	Position-2	90	156
Personnel-41	Branch-2	Rank-6	92	95.78	3.65	0.79	0	PhD	No Course	Position-3	94	315
Personnel-42	Branch-1	Rank-3	84	95.56	1.98	0.84	3	PhD	Two or More Courses	Position-2	98	125
Personnel-43	Branch-6	Rank-4	85	99.85	2.78	0.00	0	PhD	Two or More Courses	Position-3	83	195
Personnel-44	Branch-3	Rank-2	69	95.34	2.16	0.13	0	Master	No Course	Position-2	73	40
Personnel-45	Branch-1	Rank-3	97	96.05	2.34	0.27	14	Master	One Course	Position-2	79	138
Personnel-46	Branch-3	Rank-1	63	98.76	0.60	0.12	2	Master	One Course	Position-3	75	22
Personnel-47	Branch-1	Rank-5	65	99.10	1.95	0.18	0	Master	One Course	Position-1	68	257
Personnel-48	Branch-3	Rank-2	92	100.00	1.78	0.00	9	Master	Two or More Courses	Position-1	76	87
Personnel-49	Branch-2	Rank-4	91	98.92	2.45	0.00	0	PhD	No Course	Position-1	85	213
Personnel-50	Branch-6	Rank-1	61	100.00	2.63	0.00	0	University	One Course	Position-3	79	23

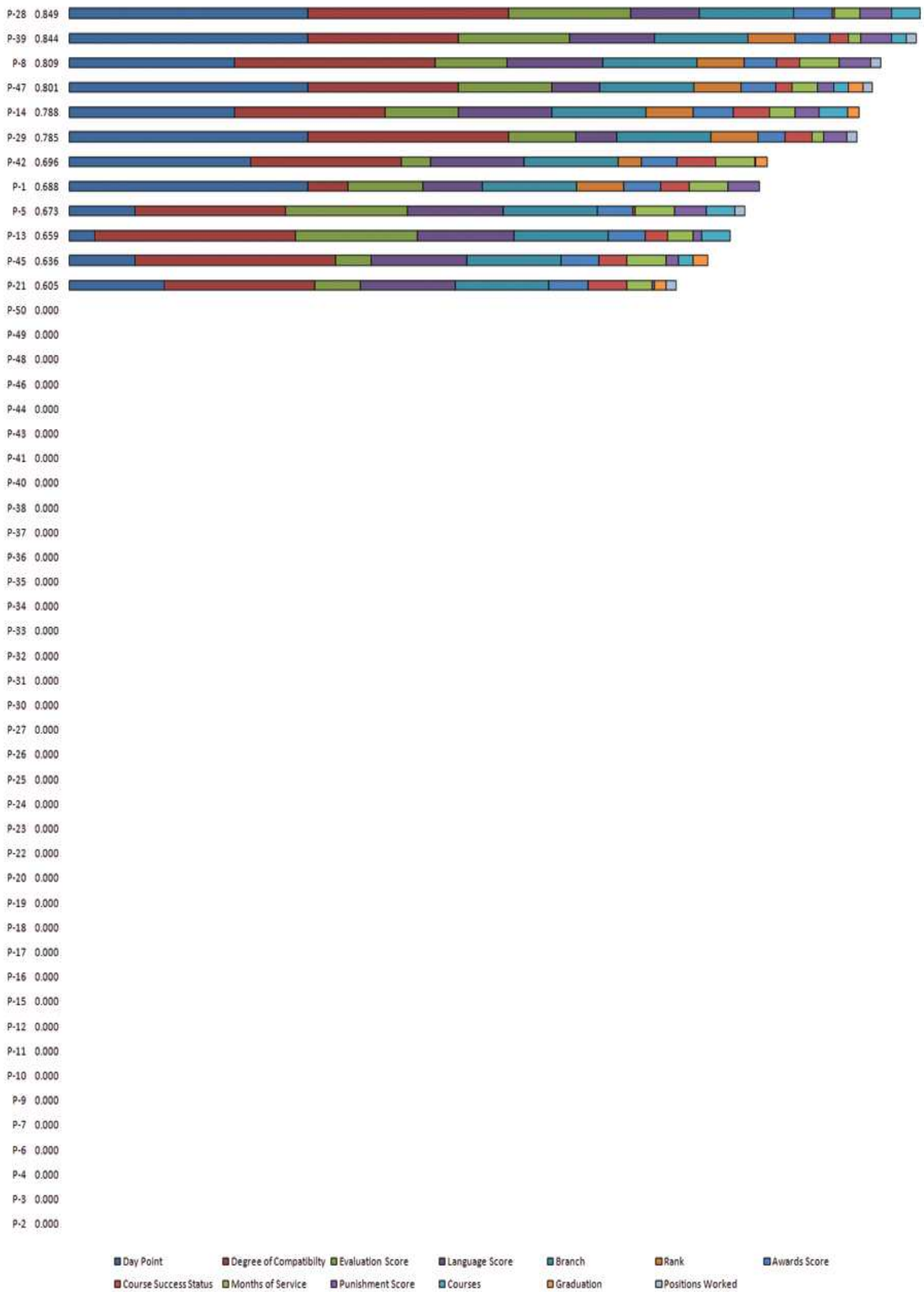

Figure 4.1: Course 1-2 Ranking

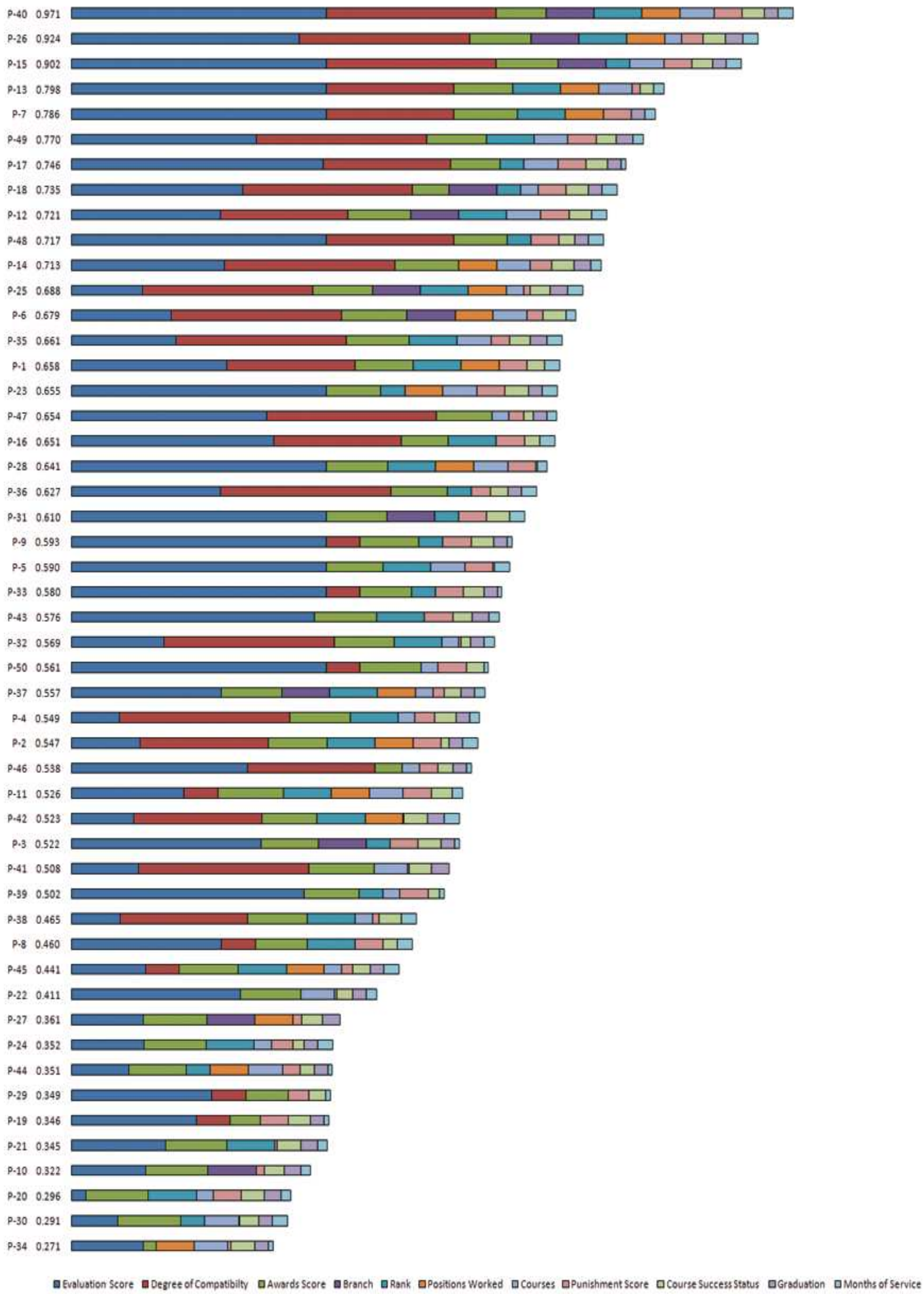

Figure 4.2: Course 3 Ranking

4.4 Benefit/Cost Ratio

In order to find benefit/cost ratios, cost data was generated for each course. The cost table for courses is shown below. These are the cost of a course for a given personnel who was assigned that course. As was mentioned before it is assumed that these costs are the same for all personnel within the same course.

Table 4.4: Cost of Courses

Costs of Courses (in dollars)			
Course-1	500	Course-11	400
Course-2	500	Course-12	340
Course-3	240	Course-13	340
Course-4	400	Course-14	340
Course-5	320	Course-15	380
Course-6	320	Course-16	460
Course-7	430	Course-17	300
Course-8	240	Course-18	300
Course-9	420	Course-19	410
Course-10	400	Course-20	390

The personnel scores for each course show us the benefits of assignments for the TURAF. Hence the benefit/cost ratios are found by dividing the personnel scores by the related cost. Those benefit/cost ratios are going to determine the overall value of Sub-problems. Instead of the values, goodness of the personnel pool and goodness of

the model can provide more insights to the DM. Although the values are not worth enough to think as goodness, the remarkable numbers are better to show to the DM. Therefore benefit/cost ratios are normalized by dividing the maximum benefit/cost ratio of the matrix. The normalized benefit/cost ratios are shown in Table 4.5.

4.5 Optimization and Results

The MATLAB code described in Chapter 3, which is based on the Jonker-Volgenant Algorithm, is used for the optimization phase. The assignment matrix, and normalized benefit/cost ratio matrix, are the inputs for the MATLAB calculation. The results of the optimization matchings are shown in Table 4.6.

The maximum value that can be reached by these costs was found by Equation 3.7, and the maximum value that we can reach by these costs and personnel was found by Equation 3.8.

$$\text{Maximum Value by Cost} = 13.862$$
$$\text{Maximum Value by Cost and Personnel} = 12.280$$

These results show that the goodness of personnel pool has 88.59% of maximum value, which means a good set of personnel is available. Looking at the results of Sub-problem(2), since we have a high percentage of achievable value, it appears that the algorithm also works well. When a good set of personnel are not available, i.e there is low overall value, some other course of actions may need to be implemented to get

Table 4.5: Normalized Benefit/Cost Ratios

	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20
P-1	0.340	0.340	0.677	0.499	0.468	0.468	0.000	0.736	0.416	0.530	0.530	0.396	0.396	0.396	0.367	0.000	0.447	0.447	0.421	0.347
P-2	0.000	0.000	0.563	0.281	0.000	0.000	0.347	0.568	0.295	0.373	0.373	0.319	0.319	0.319	0.364	0.000	0.359	0.359	0.308	0.286
P-3	0.000	0.000	0.538	0.524	0.000	0.000	0.000	0.620	0.354	0.372	0.372	0.484	0.484	0.484	0.458	0.000	0.445	0.445	0.348	0.510
P-4	0.000	0.000	0.566	0.339	0.000	0.000	0.000	0.382	0.372	0.314	0.314	0.330	0.330	0.330	0.417	0.000	0.257	0.257	0.401	0.335
P-5	0.356	0.356	0.608	0.371	0.456	0.456	0.000	0.608	0.335	0.439	0.439	0.513	0.513	0.513	0.434	0.000	0.513	0.513	0.428	0.361
P-6	0.000	0.000	0.699	0.208	0.000	0.000	0.000	0.477	0.364	0.332	0.332	0.276	0.276	0.276	0.219	0.000	0.470	0.470	0.324	0.349
P-7	0.000	0.000	0.809	0.366	0.000	0.000	0.000	0.751	0.327	0.490	0.490	0.555	0.555	0.555	0.385	0.471	0.452	0.452	0.462	0.509
P-8	0.400	0.400	0.473	0.463	0.355	0.355	0.000	0.426	0.293	0.463	0.463	0.551	0.551	0.551	0.329	0.000	0.472	0.472	0.385	0.316
P-9	0.000	0.000	0.611	0.380	0.000	0.000	0.000	0.838	0.425	0.409	0.409	0.629	0.629	0.629	0.472	0.498	0.524	0.524	0.452	0.363
P-10	0.000	0.000	0.332	0.391	0.000	0.000	0.000	0.471	0.323	0.333	0.333	0.309	0.309	0.309	0.221	0.000	0.397	0.397	0.229	0.424
P-11	0.000	0.000	0.542	0.356	0.000	0.000	0.000	0.495	0.463	0.449	0.449	0.289	0.289	0.289	0.505	0.000	0.392	0.392	0.452	0.501
P-12	0.000	0.000	0.742	0.382	0.000	0.000	0.000	0.735	0.352	0.392	0.392	0.519	0.519	0.519	0.445	0.000	0.346	0.346	0.292	0.438
P-13	0.338	0.338	0.821	0.428	0.626	0.626	0.000	0.821	0.239	0.397	0.397	0.608	0.608	0.608	0.389	0.000	0.458	0.458	0.432	0.388
P-14	0.366	0.366	0.734	0.371	0.586	0.586	0.000	0.541	0.426	0.464	0.464	0.525	0.525	0.525	0.330	0.000	0.541	0.541	0.452	0.342
P-15	0.000	0.000	0.929	0.408	0.000	0.000	0.000	0.598	0.413	0.338	0.338	0.673	0.673	0.673	0.397	0.000	0.665	0.665	0.316	0.417
P-16	0.000	0.000	0.670	0.364	0.000	0.000	0.000	0.795	0.442	0.364	0.364	0.515	0.515	0.515	0.409	0.447	0.483	0.483	0.445	0.375
P-17	0.000	0.000	0.769	0.498	0.000	0.000	0.000	0.563	0.498	0.496	0.496	0.515	0.515	0.515	0.491	0.000	0.741	0.741	0.379	0.509
P-18	0.000	0.000	0.756	0.315	0.000	0.000	0.000	0.662	0.299	0.437	0.437	0.418	0.418	0.418	0.462	0.000	0.631	0.631	0.412	0.417
P-19	0.000	0.000	0.357	0.378	0.000	0.000	0.000	0.314	0.276	0.285	0.285	0.269	0.269	0.269	0.387	0.000	0.467	0.467	0.359	0.322
P-20	0.000	0.000	0.305	0.379	0.000	0.000	0.366	0.477	0.323	0.311	0.311	0.439	0.439	0.439	0.241	0.000	0.371	0.371	0.358	0.346
P-21	0.311	0.311	0.355	0.382	0.493	0.493	0.000	0.528	0.232	0.382	0.382	0.475	0.475	0.475	0.341	0.000	0.411	0.411	0.321	0.381
P-22	0.000	0.000	0.423	0.426	0.000	0.000	0.000	0.508	0.492	0.426	0.426	0.335	0.335	0.335	0.377	0.000	0.395	0.395	0.349	0.456
P-23	0.000	0.000	0.674	0.397	0.000	0.000	0.000	0.693	0.400	0.457	0.457	0.679	0.679	0.679	0.407	0.000	0.527	0.527	0.367	0.399
P-24	0.000	0.000	0.362	0.416	0.000	0.000	0.387	0.603	0.347	0.348	0.348	0.306	0.306	0.306	0.377	0.000	0.382	0.382	0.380	0.247
P-25	0.000	0.000	0.709	0.244	0.000	0.000	0.000	0.579	0.280	0.368	0.368	0.371	0.371	0.371	0.387	0.000	0.421	0.421	0.262	0.343
P-26	0.000	0.000	0.952	0.352	0.000	0.000	0.000	0.692	0.225	0.362	0.362	0.543	0.543	0.543	0.309	0.000	0.609	0.609	0.287	0.428
P-27	0.000	0.000	0.372	0.269	0.000	0.000	0.000	0.478	0.149	0.239	0.239	0.342	0.342	0.342	0.284	0.000	0.440	0.440	0.233	0.171
P-28	0.431	0.431	0.660	0.446	0.638	0.638	0.000	0.837	0.415	0.446	0.446	0.577	0.577	0.577	0.382	0.000	0.432	0.432	0.516	0.508
P-29	0.365	0.365	0.359	0.351	0.319	0.319	0.000	0.359	0.344	0.351	0.351	0.304	0.304	0.304	0.413	0.000	0.460	0.460	0.409	0.371
P-30	0.000	0.000	0.300	0.229	0.000	0.000	0.000	0.385	0.282	0.258	0.258	0.309	0.309	0.309	0.313	0.339	0.501	0.501	0.334	0.208
P-31	0.000	0.000	0.629	0.309	0.000	0.000	0.000	0.706	0.444	0.338	0.338	0.420	0.420	0.420	0.352	0.000	0.567	0.567	0.436	0.323
P-32	0.000	0.000	0.586	0.407	0.000	0.000	0.000	0.591	0.402	0.339	0.339	0.311	0.311	0.311	0.392	0.000	0.311	0.311	0.468	0.361
P-33	0.000	0.000	0.597	0.399	0.000	0.000	0.000	0.521	0.433	0.335	0.335	0.577	0.577	0.577	0.452	0.000	0.565	0.565	0.312	0.312
P-34	0.000	0.000	0.279	0.449	0.000	0.000	0.446	0.331	0.277	0.381	0.381	0.335	0.335	0.335	0.314	0.000	0.212	0.212	0.381	0.298
P-35	0.000	0.000	0.681	0.403	0.000	0.000	0.000	0.617	0.334	0.372	0.372	0.482	0.482	0.482	0.355	0.000	0.440	0.440	0.450	0.360
P-36	0.000	0.000	0.645	0.357	0.000	0.000	0.000	0.447	0.315	0.485	0.485	0.520	0.520	0.520	0.376	0.450	0.400	0.400	0.429	0.466
P-37	0.000	0.000	0.573	0.436	0.000	0.000	0.000	0.688	0.433	0.353	0.353	0.425	0.425	0.425	0.371	0.000	0.352	0.352	0.449	0.555
P-38	0.000	0.000	0.479	0.434	0.000	0.000	0.404	0.349	0.213	0.403	0.403	0.464	0.464	0.464	0.363	0.000	0.372	0.372	0.367	0.255
P-39	0.417	0.417	0.517	0.419	0.589	0.589	0.000	0.660	0.438	0.516	0.516	0.639	0.639	0.639	0.380	0.000	0.520	0.520	0.519	0.370
P-40	0.000	0.000	1.000	0.451	0.000	0.000	0.000	0.750	0.489	0.451	0.451	0.625	0.625	0.625	0.546	0.000	0.661	0.661	0.536	0.495
P-41	0.000	0.000	0.523	0.450	0.000	0.000	0.419	0.519	0.330	0.450	0.450	0.247	0.247	0.247	0.413	0.000	0.415	0.415	0.292	0.410
P-42	0.355	0.355	0.538	0.382	0.364	0.364	0.000	0.593	0.277	0.450	0.450	0.295	0.295	0.295	0.315	0.000	0.332	0.332	0.373	0.400
P-43	0.000	0.000	0.593	0.377	0.000	0.000	0.000	0.702	0.352	0.377	0.377	0.517	0.517	0.517	0.527	0.485	0.417	0.417	0.472	0.409
P-44	0.000	0.000	0.362	0.388	0.000	0.000	0.000	0.569	0.391	0.324	0.324	0.292	0.292	0.292	0.502	0.000	0.278	0.278	0.382	0.421
P-45	0.338	0.338	0.454	0.329	0.398	0.398	0.000	0.411	0.288	0.305	0.305	0.300	0.300	0.300	0.357	0.000	0.234	0.234	0.418	0.215
P-46	0.000	0.000	0.554	0.258	0.000	0.000	0.000	0.618	0.250	0.382	0.382	0.316	0.316	0.316	0.359	0.000	0.370	0.370	0.399	0.364
P-47	0.373	0.373	0.673	0.367	0.604	0.604	0.000	0.711	0.320	0.460	0.460	0.563	0.563	0.563	0.351	0.000	0.537	0.537	0.479	0.425
P-48	0.000	0.000	0.738	0.287	0.000	0.000	0.000	0.533	0.360	0.409	0.409	0.673	0.673	0.673	0.494	0.000	0.663	0.663	0.375	0.318
P-49	0.000	0.000	0.793	0.560	0.000	0.000	0.534	0.552	0.372	0.436	0.436	0.617	0.617	0.617	0.528	0.000	0.572	0.572	0.383	0.500
P-50	0.000	0.000	0.578	0.399	0.000	0.000	0.000	0.644	0.321	0.331	0.331	0.408	0.408	0.408	0.323	0.398	0.451	0.451	0.323	0.448

Table 4.6: Results

	Total Number of Matches	**Overall Value**	**Max. Value by Cost**	**Max. Value by Cost and Personnel**
Sub-problem 1	20	8.986	66.76%	73.18%
Sub-problem 2	20	11.933	88.65%	97.17%

better results for the TURAF. The break point for making the decision about whether a set of personnel is good or bad must be determined by the DM.

4.6 Post Optimality Analysis

To show the goodness of this model and algorithm, post optimality analysis is done with different sizes of problems. The model's speed is incomparable versus hand solving, seconds versus hundreds of hours. The speed of this methodology will allow the officials to run many "what-if" scenarios and arrive at better decisions and propose different courses to the DM.

Table 4.7: Results of 20 Courses in Different Personnel Sizes

	Personnel Size		
	1000	2000	3000
Average Solution Time (CPU time in secs)	3.181	12.057	27.083
Theoretic Maximum Value	13.862	13.862	13.862
Maximum Value of Problem	12.365	12.412	12.412
Maximum Value of Model	12.134	12.302	12.322
Goodness of Personnel Pool	89.20%	89.54%	89.54%
Goodness of Model	98.13%	99.11%	99.27%

Table 4.8: Results of 30 Courses in Different Personnel Sizes

	Personnel Size		
	1000	2000	3000
Average Solution Time (CPU time in secs)	3.176	12.011	27.049
Theoretic Maximum Value	22.073	21.811	21.811
Maximum Value of Problem	19.430	19.461	19.480
Maximum Value of Model	18.957	19.161	19.227
Goodness of Personnel Pool	88.03%	89.23%	89.31%
Goodness of Model	97.57%	98.46%	98.70%

Table 4.9: Results of 40 Courses in Different Personnel Sizes

	Personnel Size		
	1000	2000	3000
Average Solution Time (CPU time in secs)	3.161	12.015	27.053
Theoretic Maximum Value	28.764	28.764	28.764
Maximum Value of Problem	25.322	25.518	25.537
Maximum Value of Model	24.621	25.043	25.145
Goodness of Personnel Pool	88.03%	88.72%	88.78%
Goodness of Model	97.23%	98.14%	98.46%

The tables show that, personnel size has an effect on solution times. However, the solution time is still very small even for large sizes of personnel. Consistent prediction of run times is not possible as it is very dependent on the new set of personnel and courses.

Due to the large number of candidates for each course the algorithm is able to achieve a high percentage for goodness of the personnel pool. Nevertheless the DM may determine a specific cutdown point for goodness of the personnel pool and results may need to be reevaluates as necessary. When the problem is reevaluated the courses which have lowest benefit/cost ratio can be canceled course allowing assignment of more personnel to the ones which have highest benefit/cost ratios or a course can be totally canceled.

Because of the small solution times, officials can run many such scenarios. Thus they can build a best personnel pool for their courses by excluding the matches in an optimal solution one by one or all the matches in a previous run. After that, a Graphical User Interface (GUI) can be created for the DM. The DM may select the personnel whom s/he does not want to assign to any course or s/he can make specific assignments. Then officials can make the assignments which have better value for the Air Force.

V. Conclusions and Future Work

This chapter summarizes the research, and discuss the conclusions and possible future work from this research.

5.1 Summary of the Research

In the first chapter of this research, the problem is defined and objectives of the research are stated. The necessary assumptions are also stated.

The general structure of an assignment problem, multi criteria decision analysis, and decision support systems are introduced in Chapter 2. The multi criteria decision analysis methods are studied and a research contribution is shown.

The methodology and its implementation are introduced in Chapter 3. The value model is structured, value functions are created and weights are determined. Then the way of building an assignment matrix is shown and sets, parameters, and decision variables are defined. Finally the problem is formulated and a solution algorithm stated.

Chapter 4 presents the analysis phase of the research. The methodology is tested by an example. Post optimality analysis is done to show robustness of the results.

In this chapter, conclusions from the results are explained and some other courses of action are recommended for future research on the same or similar problems.

5.2 Conclusions

This research deals with building a multi criteria decision support model for the TURAF course/education planning system. It creates a value model which considers more criteria than the current system and use a computer-based algorithm to solve this problem.

The value model in this research reflects the main concerns of both TURAF instructions and SMEs. The proposed solution methodology finds the maximum number of matches in Sub-Problem(1) and maximum weighted value in Sub-Problem(2). Post optimality analysis shows the optimal solution is achieved in a reasonably short time while the current system takes weeks for assignments and it also does not look for optimality.

Most of the subsystems in human resource management, one of which them the assignment subsystem, not only need quantitative data but also qualitative data evaluation due to its unique structure. Because of the complexity of human resource management, sometimes optimization-based models may not have the operational feasibility. The military environment makes this problem more complicated due to its own rules. Therefore, flexibility in the solution and model are needed. GUIs can be created to enhance the flexibility of solutions and new software can be developed for managing all of these tools.

The TURAF has written course requirements, yet she has not put them in computer database. Thus, a course database has to be created to use this model

effectively. Moreover, the Career Planning Branch has to generate compatibility diagrams between personnel and courses. This model and solution methodology also take into account the cost which is not the same in the current process. To improve the effectiveness of both manpower and budget utilizations within the whole organization needs to be considered. To aid in seeing the big picture and provide better utilization for the Air Force, all the assignments must be done at the same time instead of course by course matching.

Although this methodology finds an optimal solution, it is still going to be an initial solution and decision support for the officials unless the whole model and solution methodology are imported to the related TURAF instructions. However, using this model and solution methodology is going to remarkably decrease the workload of officials. Also, this kind of detailed model can make the selection process more objective and reliable which may result in better personnel morale and motivation.

5.3 Future Work

For future work on the same problem or a similar problems following research can be done;

- Personnel preferences can be added to the model.
- Different multi criteria decision analysis methods can be used for the model.
- The affects of weights can be examined. Thus the importance of the criteria can be known better.

- Different sensitivity or post optimality analysis methods such as Dantzig Cut can be implemented to the problem.
- A faster solution algorithm, computer program or computer language can be researched.
- General course and education plans can be structured according to personnel data, which can be predicted by some probabilistic methods, and value model.

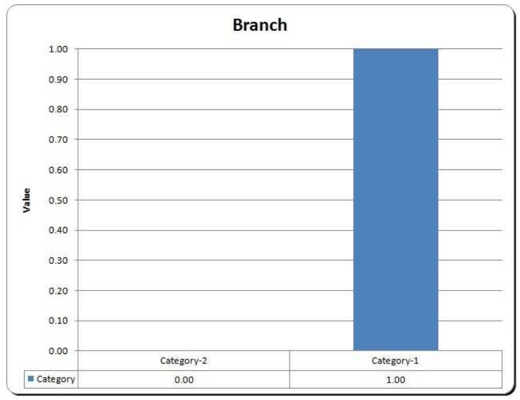

Figure A.1: Value Function of Branch

The most preferred branch or branches will be in Category-1, and the rest will be in Category-2.

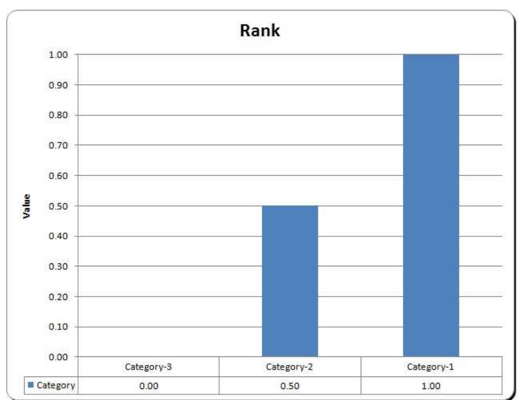

Figure A.2: Value Function of Rank

The most preferred rank/s will be in Category-1, the second preferred rank/s will be in Category-2, and the rest will be in Category-3.

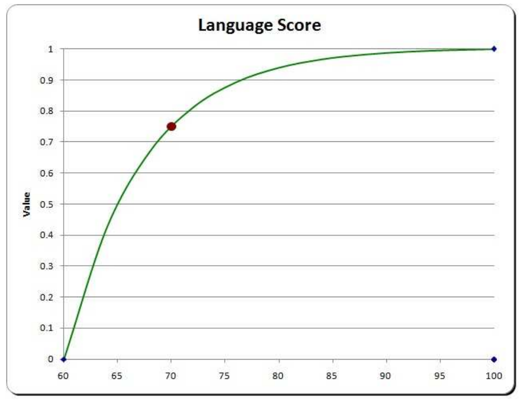

Figure A.3: Value Function of Language Score

The minimum score (60) has value of 0, the score of 70 has value of 0.75, and the score of 100 has value of 1.

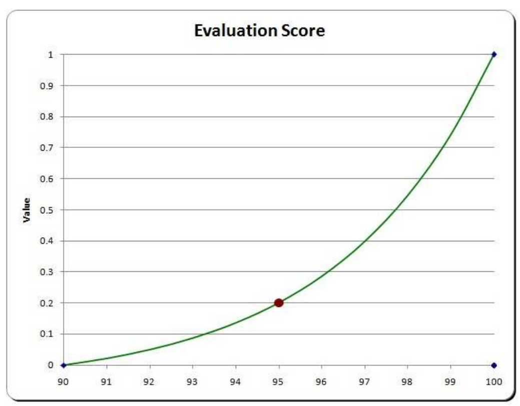

Figure A.4: Value Function of Evaluation Score

The minimum score (90) has value of 0, the score of 95 has value of 0.2, and the score of 100 has value of 1.

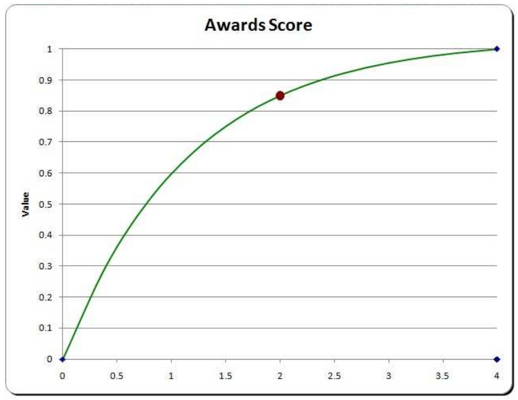

Figure A.5: Value Function of Awards Score

The minimum score (0) has value of 0, the score of 2 has value of 0.85, and the score of 4 has value of 1.

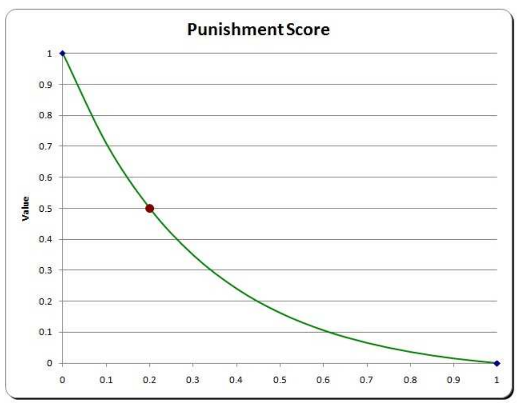

Figure A.6: Value Function of Punishment Score

The punishment score has a decreasing function. The minimum score (0) has value of 1, the score of 0.2 has value of 0.5, and the score of 1 has value of 0.

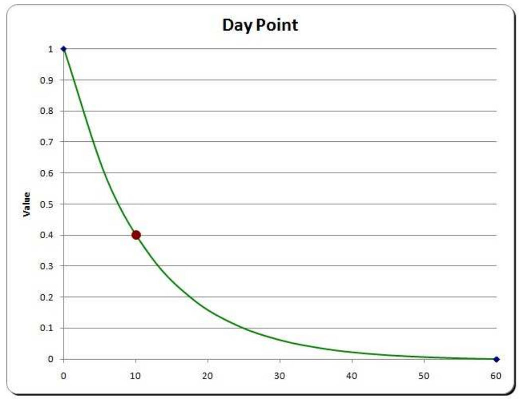

Figure A.7: Value Function of Day Point

The day point also has a decreasing function. The minimum score (0) has value of 1, the score of 10 has value of 0.4, and the score of 60 has value of 0.

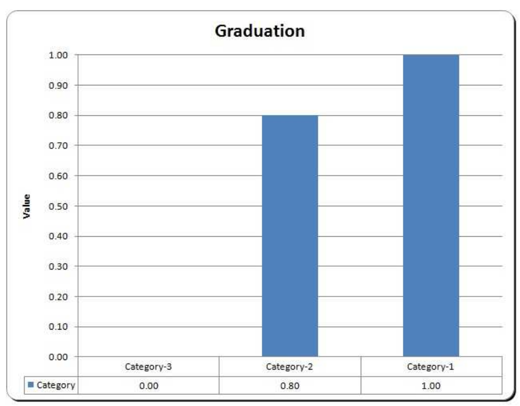

Figure A.8: Value Function of Graduation

All the Turkish officers are graduated at least from the university. Thus the candidate whose highest degree is university will be in Category-3 and has value of 0. Category-1 is the course's most preferred one, and Category-2 is the second

preferred one. That means Master Degree and PhD will be in Category-1 or Category-2 according to course's qualification.

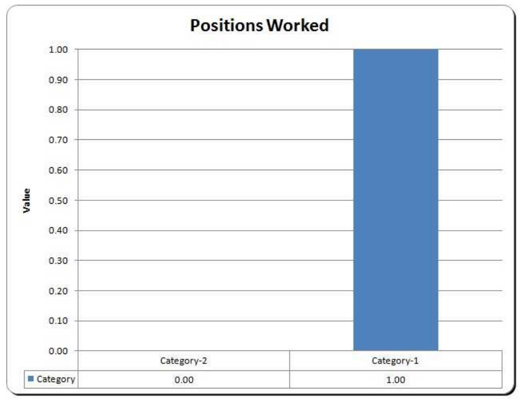

Figure A.9: Value Function of Positions Worked

We classified the positions as technical, tactical, and strategic level. The preferred position will be in Category-1 and the others will be in Category-2.

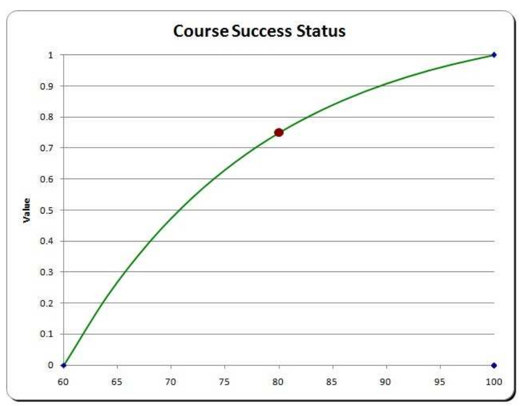

Figure A.10: Value Function of Course Success Status

Candidate has to have score over 60 for becoming eligible for the selection process. This score lays between 60 and 100. The minimum score (60) has value of 0, score of 80 has value of 0.75, and score of 100 has value of 1.

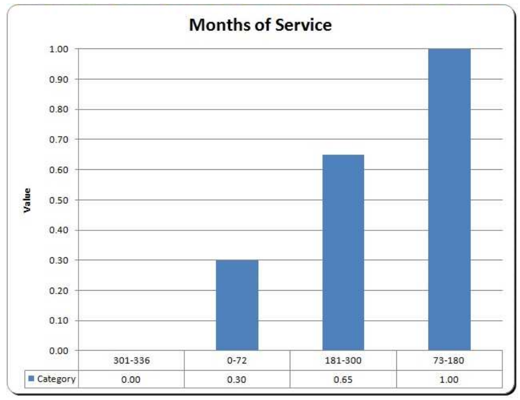

Figure A.11: Value Function of Months of Service

According to the TURAF instruction junior personnel has priority for planning for a course. The ranks of First Lieutenant and Captain are being considered as most productive times of personnel. After talking with SMEs value of 0.3 for the service between 0 and 72 months, value of 1 for the service between 73 and 180 months, value of 0.65 for the service between 181 and 300 months, and finally value of 0 for the service between 301 and 336 months are determined.

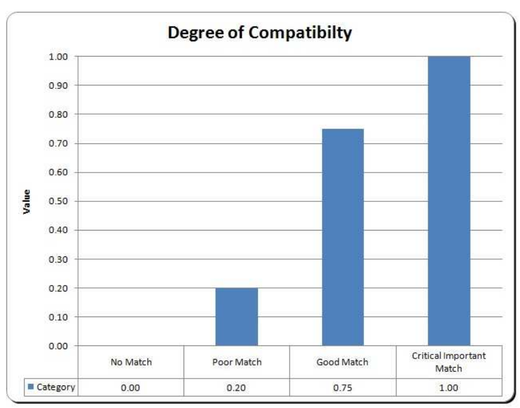

Figure A.12: Value Function of Degree of Compatibility

This value function is for degree of compatibility between a course and candidate's career path. If a course is critical important for candidate's career path then it has value of 1, if it is good match then value of 0.75, if it is poor match then value of 0.2, and if there is no match then value of 0.

Here is the MATLAB code for solving general LP problem by Jonker-Volgenant Algorithm (Cao, 2011).

```
function [matches,value,v,u,weight] = my_lapjv(weight,resolution)

if nargin<2

    resolution=eps(max(max(weight)));

end

[rdim,cdim] = size(weight);

M=min(min(weight));

if rdim>cdim

    weight = weight';

    [rdim,cdim] = size(weight);

    swapf=true;

else

    swapf=false;

end

dim=cdim;

weight = [weight;2*M+zeros(cdim-rdim,cdim)];

weight(weight~=weight)=Inf;

maxvalue=max(weight(weight<Inf))*dim+1;

if isempty(maxvalue)

    maxvalue = Inf;
```

```
end
weight(weight==Inf)=maxvalue;
v = zeros(1,dim);
matches = zeros(1,dim)-1;
colsol = zeros(dim,1)-1;
if std(weight(:)) < mean(weight(:))
    numfree=0;
    free = zeros(dim,1);
    matches = zeros(dim,1);
    for j=dim:-1:1
        [v(j), imin] = min(weight(:,j));
        if ~matches(imin)
            matches(imin)=j;
            colsol(j)=imin;
        elseif v(j)<v(matches(imin))
            j1=matches(imin);
            matches(imin)=j;
            colsol(j)=imin;
            colsol(j1)=-1;
        else
            colsol(j)=-1;
        end
```

```
        matches(imin)=matches(imin)+1;
    end
    for i=1:dim
        if ~matches(i)
            numfree=numfree+1;
            free(numfree)=i;
        else
            if matches(i) == 1
                j1 = matches(i);
                x = weight(i,:)-v;
                x(j1) = maxvalue;
                v(j1) = v(j1) - min(x);
            end
        end
    end
else
    numfree=dim-1;
    [v1 r]=min(weight);
    free=1:dim;
    [~,c]=min(v1);
    imin=r(c);
    j=c;
```

```
    matches(imin)=j;

    colsol(j)=imin;

    % matches(imin)=1;

    free(imin)=[];

    x = weight(imin,:)-v;

    x(j) = maxvalue;

    v(j) = v(j) - min(x);

end

loopcnt = 0;

while loopcnt < 2

    loopcnt = loopcnt + 1;

    k = 0;

    prvnumfree = numfree;

    numfree = 0;

    while k < prvnumfree

        k = k+1;

        i = free(k);

        x = weight(i,:) - v;

        [umin, j1] = min(x);

        x(j1) = maxvalue;

        [usubmin, j2] = min(x);

        i0 = colsol(j1);
```

```
        if usubmin - umin > resolution
            v(j1) = v(j1) - (usubmin - umin);
        else
            if i0 > 0
                j1 = j2;
                i0 = colsol(j2);
            end
        end
        matches(i) = j1;
        colsol(j1) = i;
        if i0 > 0
            if usubmin - umin > resolution
                free(k)=i0;
                k=k-1;
            else
                numfree = numfree + 1;
                free(numfree) = i0;
            end
        end
    end
end
for f=1:numfree
```

```
freerow = free(f);

d = weight(freerow,:) - v;

pred = freerow(1,ones(1,dim));

collist = 1:dim;

low = 1;

up = 1;

unassignedfound = false;

while ~unassignedfound

    if up == low

        last = low-1;

        minh = d(collist(up));

        up = up + 1;

        for k=up:dim

            j = collist(k);

            h = d(j);

            if h<=minh

                if h<minh

                    up = low;

                    minh = h;

                end

                collist(k) = collist(up);

                collist(up) = j;
```

```
            up = up +1;
        end
    end
    for k=low:up-1
        if colsol(collist(k)) < 0
            endofpath = collist(k);
            unassignedfound = true;
            break
        end
    end
end
if ~unassignedfound
    j1 = collist(low);
    low=low+1;
    i = colsol(j1);
    x = weight(i,:)-v;
    h = x(j1) - minh;
    xh = x-h;
    k=up:dim;
    j=collist(k);
    vf0 = xh<d;
    vf = vf0(j);
```

```
    vj = j(vf);

    vk = k(vf);

    pred(vj)=i;

    v2 = xh(vj);

    d(vj)=v2;

    vf = v2 == minh;

    j2 = vj(vf);

    k2 = vk(vf);

    cf = colsol(j2)<0;

    if any(cf)

        i2 = find(cf,1);

        endofpath = j2(i2);

        unassignedfound = true;

    else

        i2 = numel(cf)+1;

    end

    for k=1:i2-1

        collist(k2(k)) = collist(up);

        collist(up) = j2(k);

        up = up + 1;

    end

end
```

```
    end
    j1=collist(1:last+1);
    v(j1) = v(j1) + d(j1) - minh;
    while 1
        i=pred(endofpath);
        colsol(endofpath)=i;
        j1=endofpath;
        endofpath=matches(i);
        matches(i)=j1;
        if (i==freerow)
            break
        end
    end
end
matches = matches(1:rdim);
u=diag(weight(:,matches))-v(matches)';
u=u(1:rdim);
v=v(1:cdim);
value = sum(u)+sum(v(matches));
weight=weight(1:rdim,1:cdim);
weight = weight - u(:,ones(1,cdim)) - v(ones(rdim,1),:);
if swapf
```

```
    weight = weight';
    t=u';
    u=v';
    v=t;
end
if value>maxvalue
    value=Inf;
end
```

The following code is used for solving Sub-problem(1).

```
W=[];   %(We use our assignment matrix as Matrix W.)
A=[];
for i=1:50
    for j=1:20
        if W(i,j)==0
            A(i,j)=0;
        else
            A(i,j)=1;
        end
    end
end
weight=-1*A;
[matches,value,v,u,weight] = my_lapjv(weight);
```

```
F=[];

for j=1:20

            F(1,j)= W(matches(1,j),j);

end

result=sum(sum(F));

Assignments = matches';
```

The following code is used for solving Sub-problem(2).

```
W=[];   %(We use our assignment matrix as Matrix W.)

weight=-1*W;

[matches,value,v,u,weight] = my_lapjv(weight);

Max_Value = -1*value;

Assignments = matches';
```

Appendix C. Blue Dart

Multi Criteria Decision Support Model for the Turkish Air Force Course/Education Planning System

Personnel education is one of the most important subsystems of the human resource management system for both governmental and non-governmental organizations. Despite the changes of the war environment and the national security concept, the military is still so important for all countries. Therefore, Air Forces has to be organized with well educated personnel as all other services. Moreover, Air Forces have limited budgets and effective allocation of resources is always desired.

Personnel course/education planning process is managed by a department beneath the Personnel Directorate in the Turkish Air Force (TURAF) Headquarters and the education is separated into two sections in this department, in country and abroad. This daunting process requires a great deal of time and does not currently seek to find an optimal solution.

The TURAF is formed by different classes of personnel (e.g. officers, NCOs, civilians, specialists, etc.) and each class has different career paths and course/education planning systems. Most organizations focus on strategic level personnel education more than the others, because the variation of this level of personnel can affect the whole organization. Therefore this research focuses on the officer's course/education planning system. The TURAF has a database for all personnel information, but the officials use just a few quantitative personnel data points to complete their tasks.

Moreover, the matching process is done by hand. Therefore there is a need for a model, which supports the Decision Makers (DM), to cover the some of the other quantitative data points and also add some qualitative data for better decisions.

In this research, a value model for course/education assignments is developed. The multi criteria decision analysis method, Value Focused Thinking using the Analytic Hierarchy Process to determine value weights, is used to develop the model; and the Jonker-Volgenant Algorithm for linear assignment problems is used for the optimization phase of the problem. To take into consideration the cost, benefit/cost ratios are used in an assignment matrix. The use of the model is demonstrated by an example and the robustness of the model is tested by post optimality analysis.

The value model in this research reflects the main concerns of both TURAF instructions and subject matter of experts. The proposed solution methodology finds the maximum number of matches and maximum weighted value. Post optimality analysis shows the optimal solution is achieved in a reasonably short time while the current system takes weeks for assignments and it also does not look for optimality.

Because of the complexity of human resource management, sometimes optimization based models may not have the operational feasibility. The military environment makes this problem more complicated due to its own rules. Therefore, flexibility in the solution and model are needed and graphical user interface for the DMs can be created to enhance this flexibility. To use the proposed model effectively, the Air Force has to have databases for providing necessary data for both personnel and courses. To

improve the effectiveness of both manpower and budget utilizations within the whole organization needs to be considered. To aid in seeing the big picture and provide better utilization for the Air Force, all the assignments must be done at the same time instead of course by course matching. Although this methodology finds an optimal solution, it is still going to be an initial unless the whole model and solution methodology are imported to the related TURAF instructions. However, using this model and solution methodology is going to remarkably decrease the workload of officials. Also, this kind of detailed model can make the selection process more objective and reliable which may result with better personnel morale and motivation.

As a conclusion, this research provides a good decision support, which combines qualitative and quantitative data together, for TURAF personnel - course/education assignment problem.


Multi Criteria Decision Support Model for The Turkish Air Force Personnel Course/Education Planning System
1st Lt. Cem Malyemez (TURAF)
Advisor: Dr. Jeffery D. Weir
Reader: Lt.Col. Stephen P. Chambal, PhD
Department of Operational Sciences (ENS)
Air Force Institute of Technology
MOTIVATION & RESEARCH
Many personnel are assigned to different courses and educational opportunities in the Turkish Air Force every year. This daunting process requires a great deal of time and does not currently seek to find an optimal solution. The Turkish Air Force has a database for all personnel information, but the officials use just a few quantitative personnel data points to complete their tasks. Moreover, the matching process is done by hand. Therefore there is a need for a model, which supports the Decision Makers, to cover the some of the other quantitative data points and also add some qualitative data for better decisions.
In this research, a value model for course/education assignments is developed. The multi criteria decision analysis method, Value Focused thinking using the Analytic Hierarchy Process to determine value weights, is used to develop the model; and the Jonker-Volgenant Algorithm for linear assignment problems is used for the optimization phase of the problem. The use of the model is demonstrated by an example and the robustness of the model is tested by post optimality analysis.
E-Enlargement of mind
D-Discipline
U-Universal outlook
C-Character
A-Active habits
T-Trustworthiness
I-Ideation on the supreme
O-Omniscient grace
N-Nice temperament
Explore by Education
CONTRIBUTIONS
• The value model in this research reflects the main concerns of both the TURAF instructions and SMEs.
• The proposed solution methodology finds maximum number of matches in Sub-problem 1 and maximum weighted value in Sub-problem 2.
• The optimal solution is achieved in reasonably short time while the current system takes weeks for assignments and it also does not look for optimality.
• To see the big picture and provide better utilization for Air Force, all the assignments must have done at the same time instead of course by course matching.
• Using this model and solution methodology is going to remarkably decrease the workload of officials.
• This kind of detailed model can make the selection process more objective and reliable which may result in good personnel morale and motivation.
VALUE MODEL
Single Dimensional Value Function Examples
Weights
(Determined by AHP)
MODEL FORMULATIONS
Sub-problem 1
Max. # of Matches
Sub-problem 2
Max. Weighted Value
Goodness of Personnel Pool
Goodness of Model
INPUTS
Course Requirements
Personnel Data
Normalized Benefit/Cost Ratios
OUTPUTS
Results of Sub-problem 1 and Sub-problem 2
Achievable Values
Specific Matches
RESULTS
Maximum Value by Cost = 13.862
Maximum Value by Cost and Personnel = 12.280
Total # of Matches
Overall Value
Sub-problem 1 20 8.986
Sub-problem 2 20 11.933
Goodness of Personnel Pool = 88.59%
Goodness of Model = 97.17%
POST OPTIMALITY ANALYSIS
DEPARTMENT OF OPERATIONAL SCIENCES

Bibliography

Abu-Taleb, Maher F. and Mareschal, Bertrand. "Water resources planning in the Middle East: application of the PROMETHEE V multicriteria method". *European Journal of Operational Research*, (81):500–511, 1995.

Ananda, Jayanath and Herath, Gamini. "A critical review of multi-criteria decision making methods with special reference to forest management and planning". *Ecological Economics*, (68):2535–2548, 2009.

Barno, David W. "Near East South Asia Center for Strategic Studies". In "House Armed Services Committee, Subcommittee on Investigations and Oversight", Washington, D.C., 2009.

Brans, J.P. and Vincke, Ph. "A Preference Ranking Organization Method". *Management Science*, 31(6):647–656, 1985.

Cao, Yi. "Jonker-Volgenant Algorithm for Linear Assignment Problem". "`http://www.mathworks.com/matlabcentral/fileexchange/26836`", 2011.

Cimen, Zubeyir. *A Multi-Objective Decision Support Model for the Turkish Armed Forces Personnel Assignment System*. Master's thesis, Graduate School of Engineering, Air Force Institute of Technology (AFIT), Wright-Patterson AFB OH, 2001. AFIT/GOR/ENS/01-06.

Collette, Yann and Siarry, Patrick. *Multiobjective Optimization: Principles and Case Studies*. Springer-Verlag Berlin, Germany, 1 edition, 2003.

Dyer, James S., Fishburn, Peter C., Steuer, Ralph E., Wallenius, Jyrki and Zionts, Stanley. "Multiple Criteria Decision Making, Multiattribute Utility Theory: The Next Ten Years". *Management Science*, 38(5):645–654, 1992.

Fulop, Janos. "Introduction to Decision Making Methods". Laboratory of Operations Research and Decision Systems, 2005.

Gass, Saul I. *Linear Programming: Methods and Applications*. Danvers, Massachusetts: Boyd and Fraser, 1985.

Goemans, Michel X. “Lecture notes on bipartite matching”. ”`http://math.mit.edu/~goemans/18433S07/matching-notes.pdf`”, 2010.

Hajkowicz, Stefan, Young, Mike, Wheeler, Sarah, MacDonald, Darla H., and Young, Doug. “Supporting Decisions: Understanding Natural Resource Management Assessment Techniques”. Technical report, Land and Water Resources Research and Development Corporation, 2000.

Hajkowicz, Stefan and Higgins, Andrew. “A comparison of multiple criteria analysis techniques for water resource management”. *European Journal of Operations Research*, (184):255–265, 2006.

Hipel, Keith W. “Multiple objective decision making in water resources”. *Water Resources Bulletin*, (28):3–12, 1992.

Howard, Andrew F. “A critical look at multiple criteria decision making techniques with reference to forestry applications”. *Canadian Journal of Forest Research*, (21):1649–1659, 1991.

Janssen, Ron. *Multiobjective Decision Support for Environmental Management*. Norwell, MA: Kluwer Academic Publishers, 1992.

Jeong, Greg S. *A Multi-Objective Approach To a Bipartite Assignment Matching Problem Using Weighted Values From Multiple Constraints*. Master’s thesis, Graduate School of Engineering, Air Force Institute of Technology (AFIT), Wright-Patterson AFB OH, 2010. AFIT/GOR/ENS/10-05.

Jonker, R. and Volgenant, A. “A shortest augmenting path algorithm for dense and sparse linear assignment problems”. *Computing*, (38):325–340, 1987.

Kangas, Jyrki and Kangas, Annika. “Multiple criteria decision support in forest management - the approach, methods applied, and experiences gained”. *Forest Ecology and Management*, (207):133–143, 2005.

Keeney, Ralph L. *Value-Focused Thinking : A Path To Creative Decisionmaking*. Cambridge, Mass.: Harvard University Press, 1992.

Keeney, Ralph L. “Creativity in Decision Making with Value-Focused Thinking”. *Sloan Management Review/Summer*, 33–41, 1994.

Keeney, Ralph L. “Value-focused thinking: Identifying decision opportunities and creating alternatives”. *European Journal of Operational Research*, (92):537–549, 1996.

Koc, Mehmet F. and Erman, Halil “Telephone Interviews”. Personnel Directorate in the Turkish Air Force Headquarters, 2010.

Kolehmainen, Osmo. “Regression methods for pairwise comparisons data with applications to forestry”. ”`http://www.stat.fi/isi99/proceedings/arkisto/varasto/kole0233.pdf`”, 2010.

Korkmaz, Ibrahim, Gokcen, Hadi, and Cetinyokus, Tahsin. “An analytic hierarchy process and two-sided matching based decision support system for military personnel assignment”. *Information Sciences*, (178):2915–2927, 2008.

Lee, Sang M. and Schniederjans, Marc J. “A Multicriteria Assignment Problem: A Goal Programming Approach”. *Interfaces*, (13):75–81, 1983.

Linkov, I. and Steevens, J. “Chapter 35 Appendix A: Multi-Criteria Decision Analysis”. ”`http://www.epa.gov/cyano_habs_symposium/monograph/Ch35_AppA.pdf`”, 2010.

MathWorks Inc. “MATLAB Version 7.10.0.499(R2010a) 64 bit(win64)”.

Microsoft Office. “Home and Student 2007”.

Munkres, James. “Algorithms for the Assignment and Transportation Problems”. *Journal of the Society for Industrial and Applied Mathematics*, pages 32–38, 1957.

Murray, Williamson. “Testimony”. In “House Armed Services Committee, Subcommittee on Professional Military Education”, Washington, D.C., 2009.

Nijkamp, Peter. *Economy and ecology: Towards Sustainable Development*, chapter Chapter-12: Multicriteria Analysis: a Decision Support System for Sustainable Environmental Management. Kluwer Academic, London, 1989.

Power, Daniel J. and Sharda, Ramesh. "Model-driven decision support systems: Concepts and research directions". *Decision Support Systems*, (43):1044–1061, 2007.

Rowe, Michael D. and Pierce Barbara L. "Sensitivity of the Weighting Summation Decision Method to Incorrect Application". *Socio-Economic Planning Science*, 16(4):173–177, 1982.

Saaty, Thomas L. "A scaling method for priorities in hierarchical structures". *Journal of Mathematical Psychology*, 15(3):234–281, 1977.

Saaty, Thomas L. *The Analytic Hierarchy Process*. McGraw-Hill, New York, 1980.

Saaty, Thomas L. "Highlights and critical points in the theory and application of the Analytic Hierarchy Process". *European Journal of Operational Research*, (74):426–447, 1994.

Seo, Fumiko and Sakawa, Masatoshi. *Multiple Criteria Decision Analysis in Regional Planning: Concepts, Methods and Applications*. Reidel Publishing Co. Dordrecht, Holland, 1988.

Shim, J.P., Courtney, James F., Power, Daniel J., Sharda, Ramesh, Warkentin, Merrill and Carlsson, Christer. "Past, present, and future of decision support technology". *Decision Support Systems*, (931), 2002.

Sprague, Jr. Ralph H. and Carlson, Eric D. *Building Effective Decision Support Systems*. Englewood Cliffs, N.J. : Prentice-Hall, 1982.

Toffler, Alvin and Toffler, Heidi. *War and Anti-War*. Boston, Mass., 2nd edition, 1993.

Weir, Jeffery D. "Hierarchy Builder Version 2.0" 2008.

Weir, Jeffery D. "Multi Objective Decision Analysis Lecture Notes". Air Force Institute of Technology, 2010.

Wolsey, Laurence A. *Integer Programming*. Canada: John Wiley and Sons. Inc., 1998.

Vita

First Lieutenant Cem MALYEMEZ was born in Ardahan, TURKEY. He finished his elementary and secondary school educations in different cities of TURKEY and attended the Maltepe Military High School in 1995. He graduated from the military high school in 1999 and started his education in the Turkish Air Force Academy. He earned the degree of Bachelor of Science in Industrial Engineering after graduating from the Turkish Air Force Academy in 2003. In the same year he was assigned to Air Technical School for branch education. After this education he was assigned to 9th Main Jet Base as a personnel officer in 2004. He entered the Graduation School of Engineering, Air Force Institute of Technology in 2009.

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14. ABSTRACT

Many personnel are assigned to different courses and educational opportunities in the Turkish Air Force every year. This daunting process requires a great deal of time and does not currently seek to find an optimal solution. The Turkish Air Force has a database for all personnel information, but the officials use just a few quantitative personnel data points to complete their tasks. Moreover, the matching process is done by hand. Therefore there is a need for a model, which supports the Decision Makers, to cover the some of the other quantitative data points and also add some qualitative data for better decisions.

In this research, a value model for course/education assignments is developed. The multi criteria decision analysis method, Value Focused Thinking using the Analytic Hierarchy Process to determine value weights, is used to develop the model; and the Jonker-Volgenant Algorithm for linear assignment problems is used for the optimization phase of the problem. The use of the model is demonstrated by an example and the robustness of the model is tested by post optimality analysis.

15. SUBJECT TERMS

Multi Criteria Decision Analysis, Decision Support Model, Personnel Education, Jonker-Volgenant Algorithm, Value Focused Thinking.

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